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Abstract

Over the period 1994-2012, immigrants' wage growth in France has outperformed that of natives on average by more than 14 percentage points. This striking wage growth performance occurs despite similar changes in employment shares along the occupational wage ladder. In this paper we investigate the sources of immigrants' relative wage performance focusing on the role of occupational tasks. We first show that immigrants' higher wage growth is not driven by more favorable changes in general skills (measured by age, education and residence duration), and then investigate to what extent changes in task-specific returns to skills have contributed to the differential wage dynamics through two different channels: different changes in the valuation of skills ("price effect") and different occupational sorting ("quantity effect"). We find that the wage growth premium of immigrants is not explained by different changes in returns to skills across occupational tasks but rather by the progressive reallocation of immigrants towards tasks whose returns have increased over time. Immigrants seem to have taken advantage of ongoing labor demand restructuring driven by globalization and technological change. In addition immigrants' wages have been relatively more affected by minimum wage increases, due to their higher concentration in this part of the wage distribution.

JEL Codes: J15, J24, J31, J61, O33

Keywords: Wage dynamics, tasks, immigrants, skills

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1 Introduction

Immigrants are an important component and the main source of workforce growth in most developed countries. Not surprisingly, immigration and immigrants are at the forefront of ongoing policy debates along various dimensions. One central and often contentious issue is how immigrants fare in societies of host countries. Understanding immigrants' success is of paramount importance for the design and the sustainability of migration policies. To a large extent, this success depends on immigrants' labor market integration, which is largely the outcome of immigrants' skills and how these skills are valued in their host country labor markets. In this paper, we analyze how the relative wage performance of immigrants has evolved in France over the recent decades in relation to labor market changes (*i.e.* labor demand shifts and variation in returns to skills).

Relative wage performance and wage dynamics of immigrants are widely documented in the literature. Three factors are traditionally put forward to explain wage differences between immigrants and natives. A first factor is human capital in a broad sense, *i.e.* including schooling, experience and language skills (see Boudarbat and Lemieux (2014), Algan et al. (2010), Card (2005), Kee (1995) or Katz and Murphy (1992)).[1] A second factor refers to reservation wages. Whatever the labor market considered, immigrants are new comers. As a consequence, and beside human capital differences, they lack of host-country-specific labor market knowledge and other non directly productive valuable assets. These characteristics affect immigrants' outside option and put them in a lower bargaining position as compared to natives when they negotiate their wages with employers (see Nanos and Schluter (2014) for Germany, Moreno-Galbis and Tritah (2016) for 12 European countries, Gonzalez and Ortega (2011) for Spain, or the theoretical setups proposed by Ortega (2000) and Chassamboulli and Peri (2014)). A third factor is discrimination. Once differences in schooling, experience and reservation wages have been controlled for, an unexplained part of wage differential remains. This "migrant" effect is often attributed to discrimination (see Algan et al. (2010), Card (2005) or Kee (1995)).

Over recent decades, globalization, technological innovations and other structural changes, have induced both labor demand shifts and changes in returns to skills, leading workers to revise their occupational choices, *i.e.* workers are likely to have moved towards occupations intensive in skills whose returns have relatively increased. Beyond the traditional factors outlined in the literature, we expect changes in returns to skills and the induced changes in occupational choices to influence the evolution of the immigrant-native wage gap over time. The objective of this paper is to assess the extent to which differences in wage dynamics between immigrants and natives in France since the early 1990s are the result of different changes in returns to skills and different occupational choices.

[1] The debate is centered, on the one hand, on the role of immigrants' origin country composition and changes in the supply of traditional measures of skills as well as their portability. On the other hand, the debate also focuses on the relative deterioration of immigrants' labor market outcomes upon arrival in the host country (Borjas (1995), Friedberg (2000), Card (2005) or Dustmann, Frattini, and Preston (2013)), as well as on the progressive convergence of immigrants' wages to those of natives with years of residence in the host country (see Chiswick (1978), Borjas (1994) or Borjas (1999) for the US, Chiswick, Lee, and Miller (2005) for Australia, Friedberg and Hunt (1995) for Israel or Lam and Liu (2002) for Hong Kong).

As shown in Figure 1, based on the French Labor Force Survey, the wage growth performance of immigrants over the occupational wage ladder between 1994 and 2012 is strikingly different from that of natives (right-hand side panel), while both nativity groups have experienced the same employment dynamics over the same skill ladder (left-hand side panel). In Figure 1, occupations have been ranked in ascending order according to the median wage paid in each occupation to form 20 equal-sized (*i.e.* vigintiles) occupational employment groups.[2] The left-hand side panel of Figure 1 displays the yearly average employment growth along that skill ladder and the right-hand side panel the yearly average wage growth over the same skill ladder. Immigrants' yearly wage growth has outperformed that of natives along the whole occupational wage distribution, and particularly at the bottom tail of the distribution, where the annual difference in wage growth is around one percentage point.[3] At the top of the skill distribution, the yearly difference in wage growth is around 0.5 percentage points in favor of immigrants.[4] This higher wage growth of immigrants still arises even when controlling for changes in the population composition in terms of age, education and residence duration[5] (see Figure 2). In this case, the differential wage growth at the bottom of the wage distribution remains essentially the same as when not controlling for population composition changes, while at the top of the wage distribution this differential between immigrants' and natives' wage growth reaches almost 2 percentage points.

What is then driving the divergent wage dynamics across nativity groups? To understand this differential pattern, we propose to go beyond traditional factors studied in the literature and to investigate the role of differences in workers' (unobserved) relative skill endowments, which we proxy using the task content of occupations. The inclusion of occupations and their task content in the migration literature is relatively recent. According to the seminal Roy (1951) model, occupational specialization is due to workers' self-selection based on comparative advantages. Following that line of inquiry, Peri and Sparber (2011a), Peri and Sparber (2011b), Peri and Sparber (2009), Amuedo-Dorantes and De La Rica (2011), D'Amuri and Peri. (2014) or Basso, Peri, and Rahman (2017) underline that natives and immigrants differ in their relative skill endowments. In these studies, immigrants' and natives' unobserved skill endowments are assessed using the task requirement of occupations. A similar approach is applied by Yamaguchi (2018) on gender issues, where workers cumulate skills with experience in the task requiring those particular skills. We also build on this idea in this paper.[6] We assume that to perform the occupation-specific set of tasks,

[2]Following Autor and Handel (2013) this grouping can be viewed as a skill ladder.

[3]The divergent wage dynamics by nativity group is confirmed when estimating a quadratic equation which relates (log) wage changes to initial wages. Using a weighted least squares (weights equal native (respectively immigrant) employment in the occupation) we obtain:

$$\begin{aligned} d(\log \text{ wage}_{native}) &= -0.348 + 0.087 \cdot \log w_{1994} - 0.005 \cdot (\log w_{1994})^2 \\ d(\log \text{ wage}_{immigrant}) &= 0.291 - 0.059 \cdot \log w_{1994} + 0.003 \cdot (\log w_{1994})^2 \end{aligned}$$

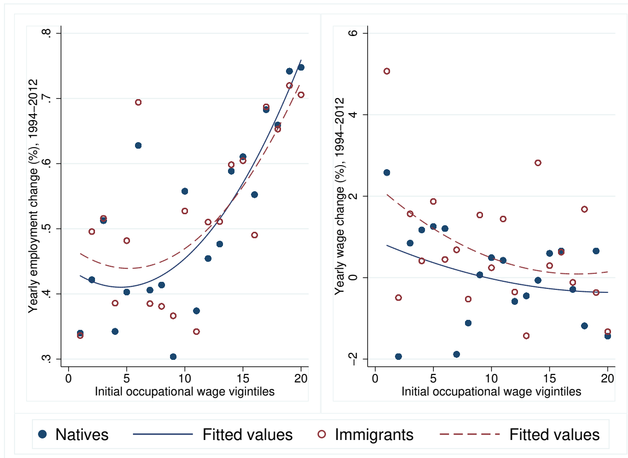
All coefficients are statistically different from zero.

[4]This finding is consistent with Mancorda, Manning, and Wadsworth (2012), who working with UK data, also show evidence of convergence in wages of immigrants and natives between 1973 and 2007.

[5]Unfortunately, our database does not contain information on language proficiency. Consistently with the findings of Lewis (2013) we proxy this variable with years of residence in the host country.

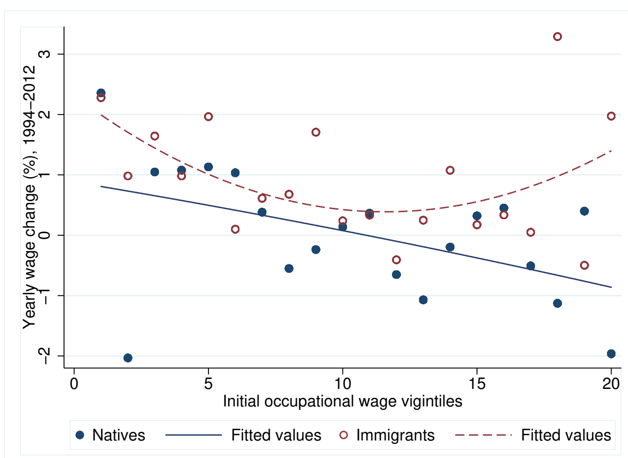
[6]This is also similar to the employer or occupation specific skill weighted approach proposed by Lazear (2009) to

Figure 1: Average employment and wage yearly growth over the 1994 median wage in the occupation. French LFS 1994-2012.



Notes: Occupations are ranked in the X-axis in ascending order according to their median real wage in 1994, computed on native full time equivalent workers, and then gathered within occupational wage vigintiles. The Y-axis in the left-hand side panel represents the average yearly employment growth between 1994 and 2012 by vigintile while on the right-hand side panel it represents the average yearly real wage growth by vigintile over the same period.

Figure 2: Average yearly wage growth over the 1994 median wage in the occupation when controlling for composition effects. French LFS 1994-2012.



Notes: Occupations are ranked in the X-axis in ascending order according to their median real wage in 1994, computed on native full time equivalent workers, and then gathered within occupational wage vigintiles. The Y-axis represents the average yearly real wage growth by vigintile over the period 1994-2012. Age*education composition is kept constant across years and equal to that of natives in 1994. Residence duration for immigrants is kept constant across years and equal to that in 1994.

workers need a bundle of different skills whose importance depends on the type of tasks. Therefore, the nature of tasks performed by workers within occupations provides useful information about their skill endowments. Since workers in different occupations perform different tasks requiring different types and levels of skills, we can relate differences in task specialization to differences in

study wage and employment mobility.

skill endowments. Thus, immigrants and natives may have different skill endowments if they are employed in occupations with different task content.[7]

The specific job specialization of immigrants could then explain specific changes in returns to skills relatively to natives. Indeed, in this setting, the same set of skills may be differently rewarded across occupations depending on the task composition of occupations. Moreover, changes in returns to skills (or changes in task prices) will affect wage changes within and across occupations (Acemoglu and Autor (2011)). For instance, cognitive skills are less rewarded in occupations intensive in manual tasks (*e.g.* movers) than in occupations relatively more intensive in abstract tasks (*e.g.* actuaries). An increase in returns to cognitive skills is expected to have a greater impact in the latter occupations, increasing wage dispersion within occupations (between a good actuary and a mediocre actuary) and also across occupations (between an average actuary and an average mover).

The originality of this paper with respect to the literature placing occupations and their task content at the heart of the wage analysis is threefold. First, contrary to most papers (see among others Peri and Sparber (2009), Amuedo-Dorantes and De La Rica (2011) or D'Amuri and Peri. (2014)), we consider wage dynamics and not wage disparities and the differential impact of immigrants on natives' wages depending on comparative advantages. Second, we estimate the impact of a common change in returns to skills on immigrants' and natives' occupational choices, which allows us to draw conclusions on the evolution of their skill endowments. This is a clear contribution with respect to the existing papers in the literature, which simply impose the relative skill endowments of immigrants (as in Peri and Sparber (2009), Amuedo-Dorantes and De La Rica (2011) and Lewis (2013) among others) or estimate returns to skills, as in Yamaguchi (2018), but do not compute changes in the occupational choices associated with the variation in returns to skills.[8] Third, while we consider wage dynamics of the aggregate pool of immigrants and natives, and not only within the arrival cohort, we propose an original approach based on both residual wages obtained from individual data and counterfactual weights to control for factors that affect the immigrant wage dynamics (such as origin country, education, age, years since arrival and sectoral sorting).[9]

For our purpose, we use the yearly French Labor Force Survey (LFS) between 1994 and 2012.[10] We start from individual data to compute residual wages, *i.e.* the part of wages that remains unexplained once we control for wage differences due to differences in age, education, years of residence in France and origin country. So we remove individual wage differences which are not specifically related to their occupation. Then, we gather these residual wages by deciles within

[7]A major limitation of this migration literature placing occupations and their task content at the heart of the economic analysis is that task content of occupations is assumed time-constant. This assumption is preset by the data sources used (such as O*NET). While we acknowledge this limitation, time-constant task composition of occupations affects both natives and immigrants. Since we are analyzing the differential wage dynamics between both nativity groups, we should be less concerned by this data limitation.

[8]In its conclusion Yamaguchi (2018) actually acknowledges that it would be important to estimate the occupational choices fostered by changes in returns to skills.

[9]Because we do not have detailed data on employers we cannot control for firm sorting.

[10]For an analysis on other European and OECD countries, see Dustmann and Glitz (2011) for OECD, Dustmann, Frattini, and Preston (2013) for the UK, Lehmer and Ludsteck. (2015) for Germany, Rodrriguez-Planas and Nollenberger (2014) for Spain. See Aleksynska and Tritah (2013) for a comparative perspective across Europe and Algan et al. (2010) for a comparison between France, Germany and UK.

each occupation to form occupation-specific residual wage distributions, which will be the base of our analysis. We apply counterfactual weights to this occupation wage distribution so that to keep population composition within occupations constant in terms of age, education and residence duration.

We can then quantify and qualify first the "price effect". To do so, we analyze the wage dynamics of immigrants and natives along the wage distribution of occupations, conditionally on the fixed set of tasks they were initially performing. The implicit idea is that, given a set of individual characteristics (especially age, education and residence duration), individuals located in the same position (*i.e.* decile) of the wage distribution of an occupation at different moments of time are likely to have similar skills. Therefore, we can relate wage changes over time in occupation-specific wage deciles (within and across occupations) to changes in occupation-specific returns to skills. This allows us to quantify a pure "price effect", since we keep constant population composition – in terms of age, education and residence duration – using a reweighting approach. Then, we qualify this effect by assessing the contribution of returns to tasks to the relative wage change of immigrants and natives.[11]

In a second stage, we relax the assumption of constant skill distribution within occupations and study how the latter has evolved among immigrants and natives between 1994 and 2012. Our aim here is to quantify and qualify this "quantity effect", while keeping constant the population composition in terms of age, education and residence duration. To quantify it, we estimate how immigrants' and natives' occupational choices have reacted to the previously estimated "price effect". We do so using an occupational choice model. To qualify the "quantity effect", we then relate immigrants' and natives' sorting across occupations to the task content of these occupations.[12] The pattern of immigrants' and natives' occupational sorting across occupations allows us to characterize changes in task specialization that drive immigrants' and natives' relative wage performance over time. Additionally, because of the specificity of the French case, we assess the role of changes in the minimum wage over the period. Unlike many developed countries, the minimum wage in France has increased at a higher pace than the average wage. Immigrants' and natives' relative wage dynamics may have been strongly affected by these minimum wage changes, given the significant share of minimum wage earners in the French labor force (11% in the early 1990s).

We find that immigrants' wage growth performance over the period is essentially due to their specific occupational employment dynamics rather than specific changes in the valuation of their skills. This suggests different changes in comparative advantages across nativity groups over the period. Therefore, the immigrants' pattern of task specialization over time is a key driver of their relative wage performance. We also uncover specific sources of wage mobility along the skill

[11] We do so under the assumption that the task content of occupations can be related to workers' skill endowments. For instance, an occupation scoring high in the index of non-routine abstract tasks will require relatively more non-routine abstract skills (such as analytical or managerial skills) than occupations having a lower score along that dimension.

[12] Basso, Peri, and Rahman (2017) use also occupational choices of high and low qualified immigrants and natives to infer the evolution of the supply of manual, routine and analytical tasks in the US following the diffusion of computers.

distribution. Indeed, the wage growth premium of less and more skilled immigrants is explained by different factors. For the least skilled, changes in skill prices brought about by minimum wage changes appear as a dominant factor. Instead, changes in relative skill endowments and returns to skills are the main factors among more skilled immigrants.

The rest of the paper is organized as follows. Section 2 presents the data. In Section 3, we provide some motivating evidence. In Section 4, we propose a conceptual setup to derive an empirical measure of the "price effect"(and present the assumptions under which this effect can be econometrically identified) and to define the "quantity effect". We develop the econometric approach and present the main results in Section 5. In Section 6, we provide some further robustness tests. Section 7 concludes. We relegate additional results to an extended appendix.

2 Data

2.1 The French Labor Force Survey

The French Labor Force Survey (LFS) was established as an annual survey in 1982. Redesigned in 2003, it is now a continuous survey providing quarterly data. Participation is compulsory and it covers private households in mainland France. All individuals in the household older than 15 are surveyed. The LFS provides detailed information on individual characteristics of the respondent and in particular on her country of birth. The latter information is used to identify natives and immigrants in this paper.[13]

The main topics covered by the LFS concern employment, unemployment, hours of work, wages, duration of employment and unemployment (length of service), discouraged workers, industry, occupation, status in employment, education/qualification, and secondary jobs. There is no much information on employers since the worker is simply asked to indicate the approximative size of his employer (the questionnaire proposes several size-intervals). Moreover, for some years this variable is poorly informed. The LFS provides also information on occupations among a list of four digit detailed occupations such as "gardener", "messenger", "clerk in banking activities", or "financial manager". We exclude farmers, civil servants, the military and clergymen from the sample.

Throughout the period, some jobs may have disappeared, while new ones have emerged. The French LFS modified the job classification in 2003 in order to take into account the changes in occupations. We pay attention to having a consistent definition of jobs throughout the 18 years of our sample. There are no new occupations that cannot be included in the pre-2003 classification. Overall we end up with 350 occupations consistently defined over the whole period.

[13] The quarterly sample is divided into 13 weeks. From a theoretical point of view, the sampling method consists of a stratification of mainland France into 189 strata (21 French regions $\times$ 9 types of urban unit) and a first stage sampling of areas in each stratum (with different probabilities, average sampling rate = 1/600). Areas contain about 20 dwellings and among them only primary residences are surveyed. Each area is surveyed over 6 consecutive quarters. Every quarter, the sample contains 6 sub-samples: 1/6 of the sample is surveyed for the first time, 1/6 is surveyed for the second time, ..., 1/6 is surveyed for the 6th (and last) time. When it was run as an annual survey, every year a third of the sample was renewed meaning that each individual was interviewed only 3 times. The collection method has always been a face-to-face interview. However, since 2003, a telephone interview has been employed for intermediate surveys (2nd to 5th).

Because the paper focuses on wage dynamics we consider only individuals for which there is information on wages. For the whole period 1993-2012 we have more than 714,000 observations. Immigrants represent every year around 11% of the considered sample. They are an average slightly older[14], earn a slightly lower average real wage, and are less educated than native workers.[15] The most numerous nativity groups are North-Africans, followed by South-Europeans and then Africans. See Tables 3 and 4 in Appendix A.1 for further details on the sample.

2.2 The O*NET and EurOccupations databases

The O*NET index is provided by the Department of Labor's Occupational Information Network. For the United States (U.S.), the O*NET database provides a detailed description of workers, occupations or jobs. We use information about occupation requirements that detail typical activities required across occupations to summarize the specific types of job behavior and tasks that may be performed within occupations.

The O*NET index is built according to the American Standard Occupational Classification (SOC). We take the task content of occupations in France to be similar to the U.S. so we can use the O*NET classification to analyze the task content of French occupations. Indeed, for our purpose, it is sufficient to suppose that there are not systematic differences between France and U.S. in the ranking of occupations. Thus, an occupation ranking high in one dimension in the U.S. also ranks high in the same dimension in France.[16] The whole issue was to link the O*NET occupation classification with the French PCS-ESE classification. To do so, we build a mapping table from PCS-ESE to SOC 2010 using the EurOccupations database, which covers 1,594 occupational titles within the ISCO-08 classification.[17] We match the 412 French PCS-ESE occupational classification

[14]Note that we are not considering the arriving cohort of immigrants, but the whole stock stock of immigrants having a positive wage (*i.e.* employed). Many immigrants start their labor market careers in the host country relatively late with respect to natives, which may justify why when considering the whole stock of immigrants we find that they are an average older, since they need to work until late in the life cycle to become eligible to the retirement pension.

[15]France has a long history of immigration. Since 1974, immigration policy is mostly based on family reunification with very little official labor related immigration. Overall and in comparison to other European countries immigration policy has taken an increasingly restrictive course. Immigration situation has been strongly influenced to the present day by the legacy of colonialism and the economic and political situation in Southern Europe (Spain and Portugal). Few recent studies have analyzed the impact of immigrants on standard natives labor market outcomes (see Edo and Toubal (2015), Ortega and Verdugo (2014) or Mitaritonna, Orefice, and Peri (2017))

[16]In the extended version of their paper, Laffineur and Mouhoud (2015) use the German "Qualification and Career Survey" to build occupational task indexes that they apply to the French professional classification of occupations. They take as starting point the estimations of Tidjens, Ruijter, and Ruikter (2011) who, working with 8 European countries (among which Germany and France), find that tasks performed in occupations in these countries are similar. Laffineur and Mouhoud (2015) show that differences between estimates using the German "Qualification and Career Survey" and those using O*NET cannot be attributed to differences in the task content of occupations between the U.S. and Germany (and thus France). They keep estimates from the O*NET index since the O*NET allows to have more details on task intensity over a bigger range of tasks.

[17]The EurOccupations project aimed at building a publicly available database containing the most common occupations in a multi-country data collection. The database includes a source list of 1,594 distinct occupational titles within the ISCO-08 classification, country-specific translations and a search tree to navigate through the database. It also provides a mapping table between the EurOccupations classification and the ISCO-08 classification, as well as a French translation of these occupations. We are very grateful to Professor Kea Tijdens for having allowed us to use this database.

for which there is at least a perfect pair with occupations described in the EurOccupations database. Finally, we use a mapping table from the ISCO-08 to the SOC- 2010 classification to link PCS-ESE occupational classification with SOC-2010. By creating this mapping table, we can use the O*NET index to analyze the task content of French occupations.

O*NET provides information on the characteristics of nearly 900 occupations in its latest version. These characteristics are listed in seven broad categories : abilities, interest, knowledge, skills, work activities, work context, and work value. We focus on work activities which are closest to the notion of task. This file gives a score ranking from 0 to 100, for 41 different tasks, indicating the degree (or point along a continuum) to which a particular descriptor is required or needed to perform the occupation. Because the O*NET database does not provide information on workers, we are unable to follow the evolution of task requirements within a given occupation.[18] We are aware of this limitation. Note though that our objective is to analyze the differential wage dynamics of natives and immigrants. Given that the time-constancy of occupations' task content affects both, immigrants and natives, we should not be very concerned by this limitation.

From the 41 tasks in O*NET, we use the strategy of Autor, Levy, and Murnane (2003), which consists in breaking down the different tasks in broad categories, based on the Dictionary of Occupational Titles (DOT) provided by the US Department of Labor. The five original categories are: non-routine manual tasks, routine manual tasks, routine cognitive tasks, non-routine analytical tasks, and non-routine inter-personal tasks.[19] Following Autor, Katz, and Kearney (2008) and Autor and Dorn (2013), we proceed to addition clusters between these categories and consider then three broad categories : non-routine manual tasks, routine (manual and cognitive) tasks, and non-routine (analytical and inter-personal) tasks. Once aggregated, we normalize these task indices.[20] The last category corresponds to what Autor, Katz, and Kearney (2008) define as "abstract tasks", *i.e.* tasks performed by educated professionals and managers that require cognitive and interpersonal skills. Routine tasks refer to the clerical and routine cognitive and mechanical skills implemented in many middle-educated white collar and manufacturing production jobs. Non-routine manual tasks are performed in many "low-skilled" service jobs such as health aides, security guards, orderlies, cleaners, and servers. These manual tasks demand interpersonal and environmental adaptability.

We do not distinguish between analytical and inter-personal tasks, within abstract tasks, essentially for statistical reasons. As pointed out by Yamaguchi (2018), it is difficult to identify separately their effects on wages using the DOT, because of their strong correlation. In addition, Yamaguchi (2010) underlines that inter-personal tasks may be not adequately measured by the DOT variables, "because the tasks of low-paying service occupations records high ratings", leading to a non-significant

[18]This exercise is done in Atalay et al. (2018). Using the text from job adds, the authors construct a data set of occupational content from 1960 to 2000. They document the importance of within-occupation task content shifts in accounting for the recent decrease in routine tasks.

[19]Appendix A.2 summarizes the content of each of the five tasks considered in Autor, Levy, and Murnane (2003).

[20]For instance, using a two digit classification of occupation; relatively to blue collars, professionals (lawyers, doctors, etc.) perform tasks that are less non-routine manual (0.0789 vs 0.1589), more non-routine abstract (0.9106 vs 0.1795) and less routine intensive (0.1104 vs 0.1795).

or even negative effect on wages. Consistently with Autor, Katz, and Kearney (2008) and Autor and Dorn (2013), we chose to include routine cognitive and manual tasks in the same category because they both correspond to easily programmable tasks, that follow repetitive, precise and well-defined procedures.

3 Empirical Motivation

Recent migration literature places occupations and their task content at the heart of the analysis of immigrants' labor market performance in the host country (see Peri and Sparber (2011a), Peri and Sparber (2011b), Peri and Sparber (2009) or D'Amuri and Peri. (2014)).[21] Recent structural changes (related with technological innovations or globalization, among others) have modified task-specific skill returns which may have contributed to the differential wage dynamics between immigrants and natives, in two ways: (*i*) inducing different changes in the valuation of immigrants' and natives' skills if the initial task specialization differs between natives and immigrants (*i.e.* "price effect"), (*ii*) promoting different sorting across tasks in case of different comparative advantages across nativity groups (*i.e.* a "quantity effect").

In this section, we show that both the "price effect" and the "quantity effect" are actually good candidates to explain the differential wage dynamics between natives and immigrants since immigrants and natives were differently distributed across tasks (and occupations) in 1994 and immigrants' occupational sorting during 1994-2012 has differed from that of natives.

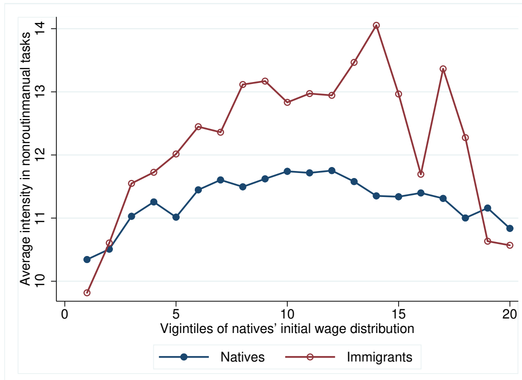
Figures 3, 4 and 5 reveal that indeed immigrants and natives differ in their task specialization. In these figures, individuals have been ranked in an ascending order into 5 percentiles wage group (20 groups) estimated on the wage distribution of natives in the initial baseline period (1994). Individuals in the same group (whether natives or immigrants) have similar level of productivity (since wages reflect productivity levels), though they have not necessarily similar skill endowments and are not necessarily in the same occupation. For each nativity group, we report on y-axis the average intensities of non-routine manual, routine and non-routine abstract tasks (*i.e.* non-routine analytical and inter-personal tasks) of their occupations.[22] Different average task intensities reflect different distribution across occupations (and thus across tasks) for immigrants and natives that are in the same location within the (native) wage distribution.

Figure 3 reveals that for an identical location in the baseline-period wage distribution, immigrants are more specialized in manual tasks. The gap in the degree of manual specialization becomes particularly large at the middle of the distribution, but it sharply drops at the top of it. Figure 4 portrays a similar picture regarding routine tasks. In this case, natives are slightly more specialized

[21] Figure 15 in Appendix C proposes a variance decomposition analysis that shows that variability of wages between and within occupation accounts for a major part of total wage variance of both natives and immigrants.

[22] These task indices are computed separately for natives and immigrants as weighted average across occupations of a given task type with weights equal to the share of immigrants or natives workers employed in each occupation in 1994. The average intensity for each task k in year 1994 is equal to $Task_{k1994} = \sum_j^J share_{j1994} * Task_{jk}$ where $share_{j1994}$ is equal to the share of occupation j in total natives or immigrants employment and $Task_{jk}$ is the intensity of occupation j in task k, where k is either (1) non-routine manual, (2) routine task (both cognitive or manual) or (3) non-routine abstract.

Figure 3: Intensity, along the skill distribution, of immigrants and natives occupational employment in non-routine manual tasks in 1994



Notes: Observations for the immigrants and natives sample are ranked in the X-axis according to their wage vigintile group (20 groups) computed over the wage distribution of natives in 1994. The Y-axis represents the weighted average of immigrants and natives occupational employment intensity in non-routine manual task within each vigintile group. The weights are equal to the share of each occupation in the total employment of the corresponding wage vigintile group, computed separately for immigrants and natives.

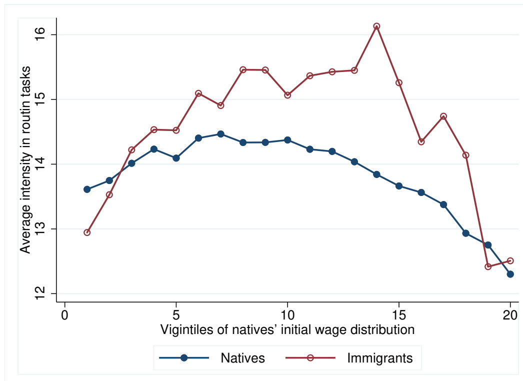
than immigrants in routine tasks at the bottom of the wage distribution. The situation is reversed beyond the third vigintile. The gap increases progressively as we move up in the distribution and then sharply falls at the top of it. The pattern of specialization is the opposite for non-routine abstract tasks (see Figure 5). Throughout the wage distribution, natives are more specialized than immigrants in this task category. The gap between the two nativity groups remains fairly stable along the wage distribution and is only slightly reduced at the top of it.

The different pattern of task specialization across nativity groups revealed by Figures 3, 4 and 5, stands for the first potential explanation of the different wage dynamics between immigrants and natives displayed in Figure 2. Specifically, immigrants' and natives' returns to skills may have evolved differently in spite of facing identical changes in returns to tasks/skills over the recent decades because of their different initial task specialization. Immigrants' and natives' skills have experienced different pricing of their skills owing to their different specialization across tasks (*i.e.* different distribution across occupations), this is what we call the "price effect".

Differences in task specialization also suggest that immigrants and natives may differ in their relative skill endowments. If this is the case, immigrants and natives may have reacted differently to changes in returns to tasks/skills, *i.e.* they have experienced a different occupational sorting. This is a second potential explanation to the differential wage dynamics between immigrants and natives that we investigate. We refer to the dynamics of sorting across occupations (*i.e.* tasks) following a change in task returns (*i.e.* skill returns) as the "quantity effect ".

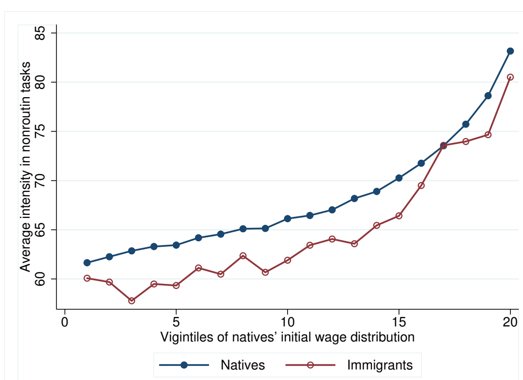
To assess the relevance of this second and complementary explanation, we report in Figure 6 changes between 1994-96 and 2010-2012 in the average task intensity of immigrants' and natives' occupational employment. As previously, the average task index is a weighted sum of a given type of task index computed across occupational employment distribution, with weights equal to the yearly

Figure 4: Intensity, along the skill distribution, of immigrants and natives occupational employment in routine manual tasks in 1994



Notes: Observations for the immigrants and natives sample are ranked in the X-axis according to their wage vigintile group (20 groups) computed over the wage distribution of natives in 1994. The Y-axis represents the weighted average of immigrants and natives occupational employment intensity in routine tasks within each vigintile group. The weights are equal to the share of each occupation in the total employment of the corresponding wage vigintile group, computed separately for immigrants and natives.

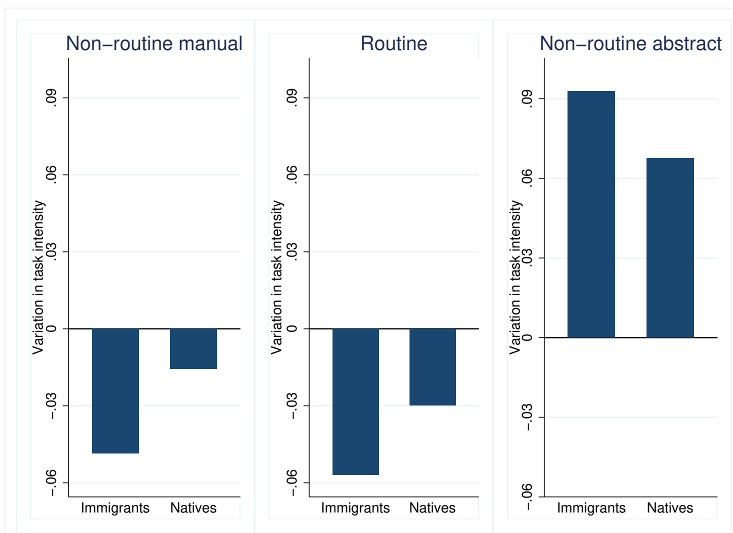
Figure 5: Intensity, along the skill distribution, of immigrants and natives occupational employment in non-routine abstract tasks in 1994



Notes: Observations for the immigrants and natives sample are ranked in the X-axis according to their wage vigintile group (20 groups) computed over the wage distribution of natives in 1994. The Y-axis represents the weighted average of immigrants and natives occupational employment intensity in non-routine abstract tasks within each vigintile group. The weights are equal to the share of each occupation in the total employment of the corresponding wage vigintile group, computed separately for immigrants and natives.

share of each occupation in total employment of immigrants or natives.[23] Between 1994-96 and 2010-12, both immigrants and natives have moved away from non-routine manual and routine task-intensive occupations (concentrated in the first half of the wage distribution) towards occupations intensive in non-routine abstract tasks (concentrated in the second half of the wage distribution). Consistently with results displayed in Figure 1, natives and immigrants have reacted in the same direction following price incitations (*i.e.* changes in returns to tasks). However, the dynamics has been clearly more pronounced for immigrants. Overall, Figure 6 suggests that occupational sorting induced by changes in returns to tasks, has contributed to a convergence in the tasks performed by immigrants and natives, even if differences persist. The pace of immigrants' task sorting portrayed in Figure 6 may have contributed to their more favorable wage growth over the period.

Figure 6: Variation in task intensity of immigrants and natives occupational employment between 1994-1996 and 2010-2012



Notes: The Y-axis represents the change between t2=2010-2012 and t1=1994-1996 in the average intensity for each task k. We compute for every year t the index $Task_{kt} = \sum_j^J share_{jt} * Task_{jk}$ where $share_{jt}$ is equal to the share of occupation j in total natives or immigrants employment and $Task_{jk}$ is the intensity of occupation j in task k =(1) non-routine abstract, (2) non-routine manual or (3) routine task. We then compute for each of the three tasks the average value of the index in 1994-1996 and in 2010-2012. Finally, we compute the variation of this index between both periods for natives and immigrants separately.

To summarize, immigrants and natives do not seem to be equally distributed across occupations (*i.e.* tasks) along the wage distribution, suggesting that both nativity groups may differ in their skill endowments. Structural changes (related to globalization or technological innovations, among others), have strongly altered returns to tasks over the past decades. These price changes should have affected differently the wage dynamics of immigrants and natives through the "price effect" and the "quantity effect" – *i.e.* the different wage changes and different occupational sorting,

[23]The average intensity for each task k in year t is equal to $Task_{kt} = \sum_j^J share_{jt} * Task_{jk}$ where $share_{jt}$ is equal to the share of occupation j in period t in total natives or immigrants employment and $Task_{jk}$ is the intensity of occupation j in task k, where k is either (1) non-routine manual, (2) routine task (both cognitive or manual) or (3) non-routine abstract.

respectively, due to divergences in relative skill endowments between immigrants and natives. We will quantify and qualify the relative importance of these two effects in the econometric analysis. In the next section, we present a simple conceptual framework providing an economic rationale to our empirical estimation. We derive an empirical definition of the components of the "price effect" and provide a definition of the "quantity effect".

4 Conceptual framework

We consider a perfectly competitive environment with exogenous wages. The production side employs labor, measured in efficiency units, as a unique production input using a linear technology (*i.e.* marginal productivity of labor equals unity). At the competitive equilibrium the price of the produced good will then equal the wage per efficient unit of labor.

On the labor supply side individuals differ on their relative skill endowments. To simplify, we focus on a particular skill S (*e.g.* cognitive skills) which is heterogeneously distributed across individuals within the interval $[\underline{S}, \overline{S}]$. We normalize to unity the remaining skill bundle (*e.g.* manual skills) and we assume that it is homogeneously distributed across workers.[24]

4.1 The occupation specific production function

The earning capacity of an individual endowed with a relative skill S_i will depend on her occupation. Indeed, task composition and relative task intensity differ across occupations. As a consequence, each occupation requires more or less quantity of S to produce one efficient unity of labor. Since wages are defined by efficient units of labor, the earning capacity of an individual endowed with S_i varies depending on the task composition of her occupation. More precisely, we consider 3 occupation categories : (i) those highly intensive in skill S (denoted H); (ii) those requiring both skills and in which tasks performed have a middle requirement in skill S (denoted M); and (iii) those weakly intensive in tasks requiring skill S (denoted L).

For a given relative skill endowment S_i the quantity of efficient units of labor, s_{ij}, provided by individual i depends on her occupation according to:

$$s_{ij} = \begin{cases} e^{\beta_L + \gamma_{Lt} S_i} & \text{for } j = L \\ e^{\beta_M + \gamma_{Mt} S_i} & \text{for } j = M \\ e^{\gamma_{Ht} S_i} & \text{for } j = H \end{cases}$$

Since we assume a linear technology, s_{ij} is also the quantity of potential output produced by a worker in each occupation. The coefficients β_j and γ_{jt} are respectively the contributions of the general skill bundle and skill S to the production of efficient units of labor in each type of job. The ratio γ_{jt}/β_j measures the relative intensity of occupation j in tasks requiring skill type S. Parameters β_j and γ_{jt} are proportional to the earning capacity of a worker in a particular occupation. Moreover,

[24] This simplification is consistent with our econometric approach where we look at the partial effect of a task dimension keeping constant other measures of task intensity. We therefore focus on relative task or skill intensity.

we assume that $\gamma_{Ht} > \gamma_{Mt} > \gamma_{Lt}$ and $\beta_L > \beta_M$. The earning capacity of skills S will then be the highest in H occupations and the lowest in L occupations, while for the complementary skill bundle we assume the opposite, its earning capacity is the highest in L jobs. Similarly to Gibbons et al. (2005) these differential weights generate a sorting of workers based on their comparative advantage.

4.2 Workers' earnings

Wages per efficient unit of labor differ from one occupation to another and returns to an identical skill endowment differ depending on the task composition of an occupation. Therefore a worker with a quantity of efficient labor equal to s_{ij} will earn a different wage depending on her occupation. Workers are paid the value of their marginal product. The wage perceived by a worker in each occupation is equal to $W_{ijt} = s_{ijt} \times p_{jt}$, for $j = L, M, H$, where p_{jt} stands for the time-varying price index of the specific goods or services provided by the occupation. With the log-specification:

$$\begin{aligned} \ln(W_{iLt}) &\equiv \omega_{iLt} = \ln(p_{Lt}) + \beta_L + \gamma_{Lt} S_i \\ \ln(W_{iMt}) &\equiv \omega_{iMt} = \ln(p_{Mt}) + \beta_M + \gamma_{Mt} S_i \\ \ln(W_{iHt}) &\equiv \omega_{iHt} = \ln(p_{Ht}) + \gamma_{Ht} S_i \end{aligned} \tag{1}$$

where p_{jt} and γ_{jt} are allowed to change over time. In this setting, conditional on a distribution of skills, the dynamics of wages (within and across occupation) and workers' occupational sorting will depend on occupation specific price changes $p_j\prime s$, and changes in occupation specific skill returns $\gamma_j' s$.

4.3 Workers' sorting across occupations

Income maximization implies that each worker chooses the job offering the highest wage given her relative skill endowment:

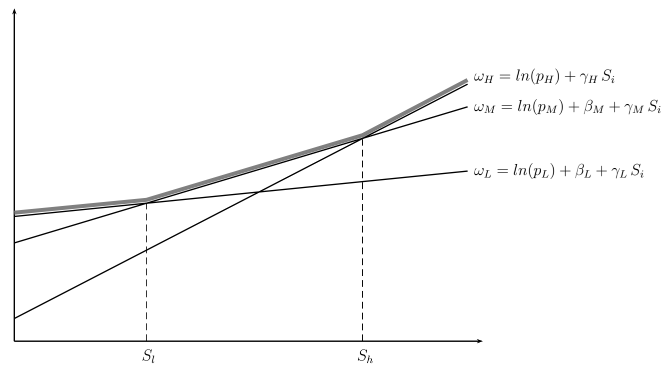
$$W^*_{ijt} = \underset{j=L,M,H}{\arg\max} \{W_{iLt}, W_{iMt}, W_{iHt}\} \tag{2}$$

We illustrate in Figure 7 one pattern of workers' sorting across the three occupations. Those with the lowest endowment of S allocate towards L occupations, where the earning capacity of skill S is the lowest and the earning capacity of the complementary bundle of skills is the highest. Workers with a medium endowment of S choose M occupations, and those with the highest endowment in S allocate towards H occupations.

Within a given type of occupation, workers are heterogeneous in terms of their skill endowment.[25] As a result, they are also earning different wages. Since workers' earning capacity is a monotonic transformation of their skill endowments, a worker position in the wage distribution within an oc-

[25]We refer to skills and not to education, therefore all potential concerns on immigrant overeducation do not apply here.

Figure 7: Wages and skill returns



cupation corresponds to her position in the relative skill endowment distribution of the occupation. We will rely on this rank-order preservation assumption in our econometric approach.

4.4 The dynamics of occupational wages

4.4.1 Parameters' identification: the "price effect"

Using this basic conceptual framework, we characterize the factors driving the dynamics of wage disparities. Individual (log) wages in a particular occupation $j = L, M, H$ are given by $\omega_{ijt} = \ln(W_{ijt}) = ln(p_{jt}) + \beta_j + \gamma_{jt} S_i$. Under the assumption of constant skill distribution within occupations, that is, under the assumption that there is no sorting of workers across occupations following changes in returns to skills, we can estimate the part of the wage dynamics corresponding to the "price effect". In our simplified Roy-type wage setting we distinguish between two determinants of wage dynamics (when the skill distribution within occupations is constant): (*i*) returns to skills (γ_{jt}), and (*ii*) a demand/supply effect inducing a change in the price of the corresponding good or service (p_{jt}). This last effect is driven by potential changes in the demand for the good/service and/or potential technological changes in the production process of the good/service.

The demand/supply effect induces wages to evolve across occupations shifting the whole wage distribution up or down. Changes in returns to skills (γ_{jt}) induce wages to evolve both within and across occupations. Occupations characterized by decreasing returns to skills will be characterized by a reduced within wage inequality and, at the same time, will move downward in the occupational wage ladder. In contrast, occupations characterized by increasing returns to skills will be characterized by greater within-occupation wage inequality and, at the same time, will move upward in the occupational wage ladder.

Because we do not have individual longitudinal data but simply a pool of cross sections[26], we assume that individuals' position in the wage distribution within a particular occupation corresponds to

[26] The French database resulting from matching individual social security data ("Déclaration Annuelle de Données Sociales") with the French Census fails to provide some of the information we require for our analysis. For example, the arrival date of the immigrant in France is only available from 1999 (and not always provided) and, especially problematic, occupations are not consistently reported.

their position on the relative skill endowment distribution of the occupation, which matches with our theoretical framework. Moreover, when interpreting our results, we will assume that, conditional on a set of observable characteristics, the skill distribution within an occupation remains constant over time.[27] We will use counterfactual weights to ensure that the age-education composition (and also the residence duration composition when working with immigrants) within every occupation is identical across periods. Under the hypothesis that the relative skill distribution within an occupation is constant, we can denote F_j the time invariant distribution of efficient units of labor, s_{ij}, in an occupation $j = L, M, H$. With a suitable normalization, the q^{th} quintile of the distribution of wages can be written as:

$$\omega_{jt}^q = \overline{\omega}_{jt} + \gamma_{jt} F_j^{-1}(q), \tag{3}$$

where $\overline{\omega}_{jt} = ln(p_{jt}) + \beta_j + \gamma_{jt}\overline{S}_{ij}$ is equal to the average (log) wage. The wage at quintile q equals the average wage in the occupation plus the marginal skill return γ_{jt} multiplied by the skill level at the corresponding quintile. Taking differences over time leads to:

$$\Delta\omega_{jt}^q = \Delta\overline{\omega}_{jt} + F_j^{-1}(q)\Delta\gamma_{jt}, \tag{4}$$

Solving for $F_j^{-1}(q)$ in (3) at the base period gives $F_j^{-1}(q) = \frac{\omega_{j0}^q - \overline{\omega}_{j0}}{\gamma_{j0}}$. Replacing in the difference equation yields:

$$\Delta\omega_{jt}^q \quad = \quad \Delta\overline{\omega}_{jt} + \frac{\omega_{j0}^q - \overline{\omega}_{j0}}{\gamma_{j0}}\Delta\gamma_{jt} \quad = \quad \Delta\overline{\omega}_{jt} + \frac{\Delta\gamma_{jt}}{\gamma_{j0}}(\omega_{j0}^q - \overline{\omega}_{j0}) \quad = \quad a_j + b_j(\omega_{j0}^q - \overline{\omega}_{j0}), \tag{5}$$

where $(\omega_{j0}^q - \overline{\omega}_{j0})$ is simply a normalization (quintiles are written in deviation from occupation average wage in the base period).

Under the hypothesis of time invariant skill distribution within occupations, we can exploit decile-specific wage changes within each occupation to identify two synthetic measures of the dynamics of wage distribution (*i.e.* "price effect") across and within occupations:

- Changes in the average wage of the occupation: the term $a_j = \Delta\overline{\omega}_{jt} = \Delta \ln(p_{jt}) + \overline{S}_{ij}\Delta\gamma_{jt}$, corresponds to the occupation-specific average wage growth (*i.e.* between-occupation wage change). This dimension of wage growth will vary across occupations due to different changes in the market price of occupation-specific goods and services and/or due to changes in the returns to skills used to perform the set of occupation-specific tasks. Immigrants and natives could experience different average wage growth along this dimension owing to their different occupational distribution and/or different skill endowments within occupations.

- Changes in wage disparities within the occupation: the term $b_j = \frac{\Delta\gamma_{jt}}{\gamma_{j0}}$ captures the within-occupation component of wage dynamics due to changes in the returns to skills. Specifically,

[27] A similar assumption is for instance exploited by Acemoglu and Autor (2011) to infer the impact of changes in task prices on wage inequality.

it measures how changes in returns to skills have impacted wage differences between workers employed in the same occupation but having different levels of skills, as measured by the occupation-specific quintile. Since returns to skills vary across tasks, immigrants and natives will experience different average returns to skills due to their different task distribution, *i.e.* occupational distribution.

Under the assumption that the relative skill distribution within occupations does not change over time, there is a clear positive correlation between average wage changes across occupations and wage changes within occupations, *i.e.* $Cov(a_j, b_j) > 0$, since both dimensions depend on returns to skills.

4.4.2 Identification issues: the "quantity effect"

Our identification strategy of the "price effect" strongly relies on the hypothesis of time-invariant skill distribution within occupations,[28] since otherwise we are not able to identify the between- and within-occupation components. This assumption is clearly inconsistent with the sorting behavior of workers across occupations, based on their comparative advantages. Selective job choices will be driven by both components of the "price effect": changes in the average wage (*i.e.* between-wage component) and changes in returns to skills (*i.e.* within wage component). The "quantity effect" refers to the part of the wage dynamics driven by the differential sorting of immigrants and natives across occupations following similar changes in price and skill returns. This section explains the "quantity effect" in more detail.

At the equilibrium, the mapping of abilities into efficient units of labor and the optimal decision rule (2) define two thresholds:

(*i*) $S_{lt} = \frac{\ln(p_{Lt}/p_{Mt})+\beta_L-\beta_M}{\gamma_{Mt}-\gamma_{Lt}}$, which corresponds to the skill level such that $W_{iLt} = W_{iMt}$, and

(*ii*) $S_{ht} = \frac{\ln(p_{Mt}/p_{Ht})+\beta_M}{\gamma_{Ht}-\gamma_{Mt}}$, which stands for the skill level such that $W_{iHt} = W_{iMt}$.

As shown by Figure 7:

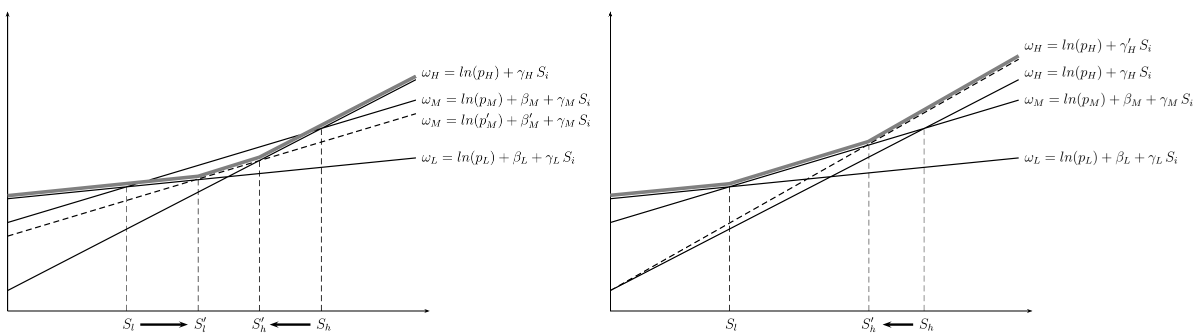
$$\begin{aligned} \text{all } i \text{ with } S_i &< S_{lt} \text{ choose the L occupation,} \\ \text{all } i \text{ with } S_{lt} < S_i &< S_{ht} \text{ choose the M occupation,} \\ \text{all } i \text{ with } S_i &> S_{ht} \text{ choose the H occupation.} \end{aligned}$$

Any exogenous variation in the price p_{jt}, or any technological change modifying the relative contribution of skills to efficient units of labor, will trigger a change in these threshold values and thus workers' reallocation across occupations, since the unitary price of their skills will be modified. For instance, a decrease in p_{Mt} (see left-hand side panel of Figure 8) increases S_{lt} and decreases S_{ht}. Workers reallocate away from M occupations towards L and H occupations. In M occupations, the lowest skilled workers (those with a weak comparative advantage in M relatively to L occupations)

[28] This hypothesis will be translated into a counterfactual reweighting procedure in our econometric approach.

reallocate towards L occupations while the highest skilled workers (those with a weak comparative advantage in M relatively to H occupations) reallocate towards H occupations. As a result, the labor share of occupations at the upper and lower ends of the skill distribution is expanding while that in the middle is contracting. Wage distribution will get more concentrated in M occupations and will widen in H and L even though returns to skills and/or skill prices have not changed in these two occupations. Similarly if returns to cognitive skills (γ_H) increase in H-type occupations (see right-hand side panel of Figure 8) there will be a decrease in S_{ht}, the highest skilled workers in M reallocate towards H jobs and thus there is an increase in wage dispersion within H-jobs. Again wage distribution will get more concentrated in M occupations.

Figure 8: Wages and skill returns



Endogenous selective sorting of workers across occupations suggests that the skill distribution within-occupations will not be fixed over time as we have assumed in order to identify $\Delta\gamma_{jt}$ and Δp_{jt}. Moreover, the direction of the bias is unclear. Depending on the exact distribution of S skills, stayers in M occupations can be on average less or more skilled than movers. For instance, if M occupations are intensive in routine tasks and H and L occupations are respectively intensive in non-routine abstract and non-routine manual tasks, following a decrease in the price of goods and services intensive in routine tasks, we will overestimate the importance of wage changes in L occupations (since new comers are relatively more skilled), and underestimate wage changes in H occupations (since new comers are relatively less skilled). Therefore, we cannot simply consider the average wage and wage dispersion changes to explain the differential wage dynamics between natives and immigrants.

To control for workers sorting, we would need to follow workers over time as in the recent contribution of Cortes (2016), to distinguish stayers from movers. Here, we only have successive cross sectional data. Therefore, and following Acemoglu and Autor (2011), we will be able to control for selection only on observable characteristics, that is we will be measuring wage changes that occur among individual being similar with respect to a fixed set of observable characteristics. We will be using counterfactual weights to compare wage changes along the wage distribution of every occupation for workers having the same observable skill distribution within occupations, which we take to be equal to that of the baseline period (*i.e.* before the change in task returns). Moreover, in order to focus on occupation-specific skills and not on general skills, whose returns may have changed, we will rely on residual wage changes as in Autor, Katz, and Kearney (2008).[29] This is important for instance if some occupations attract more educated workers and the return to education rises over time, we will otherwise measure the mechanical effect of rising returns to education instead of occupation-specific skill returns.[30]

To estimate the "quantity effect", we relax the assumption of fixed distribution of workers across tasks (and thus constant skill distribution within occupations). We estimate a conditional logit model that allows us to assess whether immigrants and natives, facing similar changes in good/service prices and skill/task returns, have followed different sorting pattern over time across occupations and tasks. This approach allows us to draw conclusions on the potential contribution of workers' selective mobility across tasks on wage dynamics.

5 Results

5.1 The price effect

In this section, we first quantify the "price effect" and then we qualify it. To quantify the "price effect", we characterize changes in wages between and within occupations using two occupation-specific parameters estimated separately on each nativity group under the assumption that the relative skill distribution within each occupation is constant. We focus on males' residual wage changes,[31] between the periods 1994-96 and 2010-12, $t = 0$ and $t = 1$, respectively.[32] Focusing on long differences helps to limit the influence of short-term variations and thus to identify long-term effects of changes in prices and skill returns on wage changes. In addition, using long differences instead of year-to-year changes avoids some serial correlation issues, which would lead the estimated standard errors to be understated (see Bertrand, Duflo, and Mullainathan (2004)). Moreover, in order to increase the number of observations per occupation, each of the two periods for which we are computing long differences includes three years of data. This was necessary since we are using a detailed definition of occupations (four digits).[33]

[29]Interestingly, we find that within- and between-occupation wage changes are positively correlated only once we focus on changes in residual wages, *i.e.* the part of wages which is not explained by observable characteristics (age, education, and residence duration and origin country in addition for immigrants). This suggests that sorting across occupations based on observable characteristics is important in our setting.

[30]Using Canadian data, Boudarbat and Lemieux (2014) find actually that both changes in the mean wage gap between natives and immigrants and changes in the gap at different quantiles of the wage distribution are explained by standard factors such as experience, education, and country of origin of immigrants.

[31]Excluding females allows to simplify the analysis because this avoids dealing with gender specificities in labor supply choices. See Edo and Toubal (2017) for an analysis on the impact of immigration on the French gender gap.

[32]Data prior to 1993 are difficult to use because of a substantial change in the French Industry Classification (NAF), that prevents us from having an unequivocal correspondence between the industry codes before and after 1993. This is a problem in our case because some jobs are defined in a specific industry. The Labor Force Survey 2012 were the most recent available data at the time of writing this paper. Note also that each period corresponds to the final part of a crisis: the nineties crisis for period 1994-1996 and the recent economic crisis for period 2010-2012.

[33]Otherwise, when working with immigrants, we would not have enough observations per occupation and per period.

In a second step, we qualify the "price effect" by comparing immigrants' and natives' wage growth performance within and across occupations conditional on a fixed task specialization. That is, we study how the estimated "price effect" may be attributed to the specific tasks performed by immigrants and natives. We implement the whole procedure with alternative sampling weights in order to control for changes in population composition that may affect changes in the structure of residual wages between periods 1994-96 and 2010-12. We use the reweighting strategy suggested by Lemieux (2002), to remove from occupational wage changes the part that results from changes in the population composition in terms of age, education and duration of residence within occupations.

5.1.1 Quantifying the "price effect": the between- and within-occupation components

We first recover residual wages $\tilde{w}_{int}$ for each period ($t = 0, 1$) in the same way as in the variance decomposition analysis presented in Appendix C. By construction, residual wages measure wage disparities which are orthogonal to other worker observable characteristics (age, education, residence duration, origin country). Working with these residual wages allows us to control for wage disparities between workers which are not specifically related to their occupation. We gather these residuals by deciles within each occupation to form occupation specific residual wage distribution (9 deciles per occupation). Second, we summarize changes in this occupation specific residual wage distribution into two components: a between-occupation and a within-occupation component. For this, we estimate the occupation-specific intercept a_j (between effect) and slope b_j (within effect) in equation (5). Specifically, we estimate a linear relationship between the residual wage change at each occupation-specific decile q, $\Delta\tilde{w}_j^q$, and the corresponding level of the wage decile q at the base period ($t = 0$), $\tilde{w}_{j0}^q$:

$$\Delta\tilde{w}_j^q = a_j + b_j\,\tilde{w}_{j0}^q + \lambda^q + v_j^q, \tag{6}$$

where v_j^q is an idiosyncratic error term. We also consider a decile-specific error component, λ^q, representing a generic change in the returns to skills, which is common across all occupations but specific to a wage decile.[34] Computing wage decile changes (*e.g.* between the 4th wage decile of actuaries in period 1 and the 4th wage decile of actuaries in period 0) requires a sufficient number of observations in each occupation.[35] Overall, we are left with 229 occupations for natives and 146 occupations for immigrants. In specification (6), we interpret the distance between wage deciles within an occupation as differences in occupation-specific skill levels. Therefore, the slope b_j (within effect) tells us whether and to what extent wages of more skilled workers in an occupation have evolved more favorably than those of less skilled workers within the same occupation. In other words, b_j captures the contribution of changes in returns to skills within an occupation to the wage

[34] This would capture for instance the effect of some labor market institutions (minimum wage, occupation level wage negotiations) which will affect more the bottom wage deciles of all occupations.

[35] In fact, each wage decile needs to be separately observed in each period. This requires at least 10 observations per period for each occupation and nativity group.

growth of that occupation. The intercept a_j (between effect) is a measure of overall occupation-specific wage growth, *i.e.* it captures shifts in the overall wage growth distribution which may come from changes in the market price of the occupation good/service or from changes in returns to skills used to perform the occupation-specific tasks.

Both b_j and a_j are separate measures of the "price effect". Both measure the shift in the occupational wage distribution and both are affected by changes in occupation-specific returns to skills, $\Delta\gamma_{jt}$. In addition, the intercept a_j depends also on changes in the price of occupation-specific goods and services, which are not directly related to changes in returns to skills.

We estimate separately the price effect (b_j and a_j) over natives and immigrants and analyze how it has contributed to the differential wage dynamics across nativity groups.[36] We gather interesting insights on this question by looking at Figure 9 (as well as Figure 19 in Appendix C). The X-axis represents the occupational wage or skill ladder (we rank occupations according to the natives residual mean wage in period 0), while Y-axis represents the between effect, a_j (left-hand side panel) and the within effect, b_j (right-hand side panel). We have used counterfactual weights to insure time-invariant population composition across and within nativity groups for each occupation. We compute the counterfactual weights using as a reference for both nativity groups the age-education composition of natives in the occupation in period 0. This baseline composition is exogenous to changes in tasks prices and skill returns which occured over the period. Additionally, for immigrants, the composition in terms of residence duration is the same as in period 0 (see Appendix B for a detailed explanation).

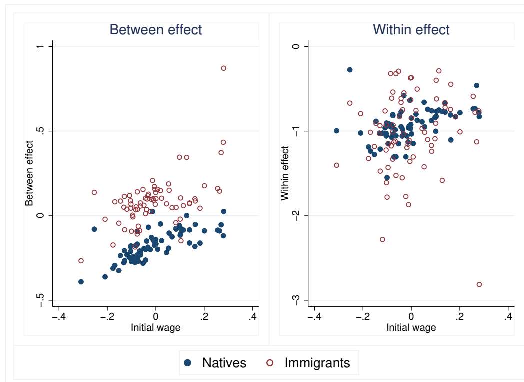
We can see that for both immigrants and natives, occupational wage growth (between effect) is higher in better paid (more skilled) occupations and it is actually higher for immigrants. As it can be seen on the right-hand side panel of Figure 9 (within effect), this pattern has been barely driven by increasing returns to skills along the skill ladder. In other words, there is no clear pattern of different changes in returns to skills within occupations between immigrants and natives. Moreover, the profile of changes in returns to skills seems to be more erratic for immigrants than for natives.[37] Overall, immigrants' average wage growth clearly outperforms that of natives across the whole occupational wage ladder. At first glance, immigrants' better relative average wage performance is due to their skill endowments rather than their different returns to skills.[38] As we shall see in the econometric analysis, part of this more favorable skill endowment may be related to dimensions which are not measurable such as occupation-specific skills, which we relate to the task content of

[36] Figures 16 - 18 in Appendix C display the relationship between a_j and b_j with the observed sample and with a counterfactual sample obtained when controlling for population composition. Interestingly, we observe a positive correlation between the two components of residual wage changes: occupations with higher overall wage growth, a_j, are also those where wage gaps between more and less skilled workers (*i.e.* high and low wage deciles) widened the most (*i.e.* larger skill returns, b_j). This is perfectly consistent with the Roy-type wage setting we outline in our conceptual framework which predicts that both components of the price effect are positively correlated *i.e.* $Cov(a_j, b_j) > 0$.

[37] These results are robust to wage differences that may be due to differences in age, education, country of birth and residence duration, and they are not driven by changes in population composition over time.

[38] To see this, note that the wage growth premium of immigrants relatively to natives within an occupation is equal to: $\Delta\bar{\omega}_{jt}^{IM} - \Delta\bar{\omega}_{jt}^{NA} = \Delta\gamma_{jt} * (\bar{S}_j^{IM} - \bar{S}_j^{NA})$, where $(\bar{S}_j^{IM} - \bar{S}_j^{NA})$ is the difference in skill endowments in occupation j between immigrants and natives.

Figure 9: The Between and Within occupation wage growth components for natives and immigrants. Constant population composition.



Notes: Natives' residual wages have been computed by including in the wage equation a full set of age*education dummies while immigrants' residual wages have been computed by including in the wage equation a full set of age*education*residence duration dummies and 27 origin country dummies. The between and within occupation wage growth components have been computed using residual wage deciles. In the X-axis occupations are ranked according to their median wage computed over the wage distribution of natives residual wage in the baseline period (1994-96). The age*education composition within occupations is kept constant and equal to that of natives in the baseline period for both immigrants and natives. For immigrants residence duration composition is also kept equal to that observed in the baseline.

occupations.[39]

Once the "price effect" is quantified, we examine in the next section to what extent this effect comes from differences in skill endowments between immigrants and natives. To do so, we will analyze how immigrant-native differences in between- and within-occupation wage changes (a_j and b_j, respectively) vary depending on the task content of the occupation. When returns to identical tasks (which proxy skills) differently contribute to the wage dynamics of immigrants and natives employed in the same occupations, this means that immigrants and natives differ in their relative skill endowments in spite of being employed in the same occupation. Next section analyzes this question in detail.

5.1.2 Qualifying the "price effect": the role of tasks

As suggested by our Roy conceptual framework, workers within the same occupation, despite having identical observable characteristics (*i.e.* age, education and duration of residence in host country) do not necessarily have the same (multidimensional) skill endowment. Therefore, even if returns to skills/tasks are identical for all workers employed in the same occupation, two workers with different skill endowments can experience different wage changes even though they are employed in the same occupation and perform the same tasks. In this case, returns to skills/tasks could differently contribute to wage changes within and across occupations. For instance, immigrant and native actuaries may earn the same wage in a base period. However, immigrant actuaries may have

[39]One systematic source of skill disparity between immigrants and natives may be due to the fact that immigrants are over-educated within occupations relatively to natives. This has been shown for the UK by Dustmann, Frattini, and Preston (2013) and across European countries by Aleksynska and Tritah (2013). While Chiswick and Miller (2010) have shown that this over-education explains the better wage performance of immigrants in low skilled occupations.

a higher level of analytical abstract skills (as compared to their communication skills), while natives have a medium level of analytical skills (as compared to their communication skills). Following an increase in returns to analytical skills, wage growth among all actuaries relatively to other occupations will increase. Nevertheless, wage growth among immigrant actuaries will outperform that of natives because of their relatively better endowment in analytical abstract skills, whose relative returns have increased the most.

We assess native-immigrant differences in skill endowments in Table 1. The coefficients a_j and b_j estimated in previous section allow us to capture the occupational wage dynamics of immigrants and natives. We collect as many coefficient estimates $(\widehat{a_j}, \widehat{b_j})$ as there are occupations employing both immigrants and natives. We do not observe workers' skills but we have information on the task content of their occupation, which we take as a proxy for the skill requirement in the occupation. If within an occupation, returns to identical tasks k contribute differently to the occupational wage dynamics (a_j and b_j) of natives and immigrants, we can guess that the skill endowment of k differs between natives and immigrants.[40] From the pooled sample of coefficient estimates for immigrants and natives, we estimate the following reduced-form relationships :

$$\widehat{a_{ji}} = \alpha_0 + \alpha_I \text{Immigrant}_i + \sum_{k=1}^{3} \alpha_k TC_{jk} + \sum_{k=1}^{3} \alpha_k^I \text{Immigrant}_i \times TC_{jk} + \mu_{ij}, \tag{7}$$

$$\widehat{b_{ji}} = \delta_0 + \delta_I \text{Immigrant}_i + \sum_{k=1}^{3} \delta_k TC_{jk} + \sum_{k=1}^{3} \delta_k^I \text{Immigrant}_i \times TC_{jk} + \nu_{ij}, \tag{8}$$

where Immigrant_i is a dummy variable taking the value 1 if the coefficient has been estimated on the sample of immigrants, 0 otherwise. TC_{jk} is the task intensity index for each occupation j and task category k = (1) non-routine abstract, (2) routine, and (3) non-routine manual. Note that task intensity indices are normalized across occupations and estimations are weighted using the size of the nativity group in the occupation.[41] Because we are using initial period weights, we insure that wage dynamic differences between immigrants and natives are not driven by changes in the occupational (or task composition) distribution over time. Coefficients α_I and δ_I capture systematic differences in wage dynamics between immigrants and natives. The coefficient α_I allows us in particular to test the existence of a wage growth premium for immigrants, as suggested in

[40] Note though that a significantly different contribution of returns to tasks to between- or/and within-occupation wage changes could be suggestive of either discrimination (*i.e.* identical skill endowments are differently rewarded) or a differential skill endowment between natives and immigrants (*i.e.* returns to skills are identical but the skill endowment differs across both nativity groups). Distinguishing these two explanations is beyond the scope of this paper.

[41] We define the "normalized" task intensity index by occupation as:

$$TC_{jk}^{norm} = \frac{TC_{jk} - \min[TC_k]}{\max[TC_k] - \min[TC_k]} \tag{9}$$

where $\min[TC_k]$ corresponds to the minimum value observed for the task index k across all considered occupations and $\max[TC_k]$ corresponds to its maximum value.

Figure 9. Coefficients α_k and δ_k measure the contribution of returns to each task k to natives' wage changes across ($\widehat{a_j}$) and within ($\widehat{b_j}$) occupations[42], while coefficients α_k^I and δ_k^I capture the contribution differential for immigrants. The latter coefficient estimates specifically allow us to test wether returns to tasks have contributed differently to the wage dynamics of natives and immigrants working in the same occupations, and thus to identify immigrant-native differences in skill endowments. [43]

We also control in our regressions for two other potential drivers of the differential wage dynamics between natives and immigrants. On the one hand, labor demand may evolve due to changes in the national output mix, and this may affect occupations differently due to their specific initial distribution across sectors. Given that immigrants and natives, within the same occupation, may be employed in different sectors, they will be differently impacted by these changes independently on their relative skill endowments. To mitigate this effect, we add in our regressions an occupation-specific labor demand shift index *à la* Bartik (1991), which is constructed from the distribution of occupations across sectors in 1994-1996 and takes into account changes in the industrial composition between periods 1994-1996 and 2010-2012.[44]

On the other hand, our estimates take into account workers' sorting on observable characteristics so as to get rid-off differential composition effects between immigrants and natives. We consider three different weighting schemes as described in the Appendix B. In the baseline scenario, we use the LFS original population sample weights; populations are therefore representative of their specific nativity group in each period. Next, we consider the weighting scheme 1, which insures a constant population composition within occupations for each nativity group separately. In that case, population in each nativity group is representative (along observable characteristics) of the baseline population of each occupation. Age*education composition is kept constant within occupations as in the base period. We therefore focus on the sub-population which is the most likely to work in an occupation before the shift in skill returns (our conceptual framework highlights that this is the right population to consider to identify the between- and within-occupation wage components). Lately, the weighting scheme 2 insures that within occupations the population composition is not time varying and is the same for both nativity groups, taking as a reference group the native population of each occupation in the base period. Age*education within each cell is kept constant and similar to that of natives in the base period. This latter weighting scheme controls for different composition effects

[42]Parameter estimates of the above equations when working separately with the native and the immigrant sample are available from the authors upon request.

[43]The fact that the dependent variable is estimated introduces measurement error and loss of efficiency, but does not, unlike measurement error in independent variable, present any difficulties for regression analysis (see Maddala (2001), p. 64, for a standard reference). These measurements errors will introduce heteroskedasticity if they are not constant across observations. We correct for this issue using White (1980)'s standard errors adjustment. Some authors have suggested weighted least square adjustment, through a series of Monte Carlo experiment. Lewis and Linzer (2005) show that the efficiency gains are in most cases very limited.

[44]We define as follows the labor demand shift indicator for occupation j and origin i: $\text{DemandShift}_{ji} = \sum_s \left[\frac{N_{sji0}}{N_{ji0}} \cdot \Delta N_{si}\right]$, where N_{sji0} stands for the number of employees in sector s, occupation j from origin i in period 0 (base period). N_{ji0} represents the total number of employees in occupation j from origin i in period 0. ΔN_{si} is the variation in the number of employees from origin i in sector s. In order to obtain the labor demand shift associated with an occupation, we must sum shifts over all sectors s composing the occupation j.

across nativity groups and over time. Additionally, for immigrants, wage residuals and weights are computed with and without controlling for residence duration (see notes at the bottom of Table 1).[45] Controlling for residence duration is important if some occupations are experiencing inflows of new immigrants, that may lack country non-observable specific human capital. Estimations that use the weighting scheme 2 and control for residence duration (columns 5 and 10) are the most consistent with the assumption of constant population composition within occupations in our Roy-type framework. Depending on the scenario, the sample size varies from 248 to 144 observations (*i.e.* 72 occupations per nativity group).

To assess the sources of differential wage changes within and across occupations, we have successively introduced the Immigrant dummy variable (see Table 6 in Appendix D), the task intensity indices (see Table 7 in Appendix D) and their interactions (see Table 1). The results obtained by including only the Immigrant dummy variable (see Table 6 in Appendix D) confirm those reported in Figure 9 : across occupations, immigrants' relative wage growth outperformed that of natives by 26% over the 20 years. This is quite substantial given that we control for observable characteristics such as age, education and residence duration. This high relative wage performance is robust to differences in observable characteristics between immigrants and natives within occupations.[46]

Table 7 in Appendix D adds the task content of occupations. The immigrants' wage growth premium (*i.e.* captured by the coefficient on Immigrant) does not seem to be driven by specific returns to skills associated with non-routine abstract, routine and manual tasks. Returns to non-routine skills (abstract and manual) have positively influenced average wage growth in occupations, while returns to routine skills have had rather a negative influence.

To test wether returns to occupation-specific tasks have contributed differently to the wage dynamics of natives and immigrants, we add in Table 1 interaction terms between the Immigrant dummy variable and the occupational task indices. Such heterogeneity arises if immigrants' and natives' skill endowments were initially different (or have changed differently over time). In other words, different skill endowments between immigrants can explain why returns to identical tasks would have differently contributed to the wage dynamics of immigrants and natives employed in the same occupations. Estimates in Table 1 reveal that most differences in task-specific returns to skills are indeed due to differences in observable skill endowments related to age, education and residence duration. The immigrants' wage growth premium is barely altered when considering potential heterogenous effects in task-specific returns to skills. There is virtually no immigrant-specific return to task that arises as significantly different from that of natives when considering changes in oc-

[45] More precisely, in weighting scheme 1, age*education*(residence duration) composition is kept constant within occupations as in the base period. In weighting scheme 2, immigrants' residence duration is kept constant within each occupation, and age*education within each (occupation*residence duration) cell is kept constant and similar to that of natives in the base period. We consider two levels of residence duration, below 10 years and above 10 years.

[46] The immigrant wage growth effect is almost twice when ignoring their observable specific characteristics (see coefficient difference between columns 4 and 5). This is an expected result that can be interpreted as follows: immigrants are on average younger and also very often over-educated. If over the period, returns to education have increased while returns to experience have decreased, then this could explain the specific wage growth premium associated with their age and education. Indeed, immigrants' more favorable returns to skills (*i.e.* within effect) are entirely due to their specific characteristics (see coefficient change between column 9 and column 10).

Table 1: Task contribution to between- and within-occupation wage changes, from 1994-96 to 2010-12. Natives vs. Immigrants.

Dependent variables: Between- and within-occupation wage changes

	Between-occupation wage change					Within-occupation wage change				
Scenarios	Baseline	Weight 1	Weight 2	Weight 1	Weight 2	Baseline	Weight 1	Weight 2	Weight 1	Weight 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Immigrant	0.209***	0.244***	0.492***	0.438***	0.238***	-0.0477	0.217	0.188	0.432***	0.0529
	(0.0571)	(0.0510)	(0.0452)	(0.0614)	(0.0507)	(0.113)	(0.146)	(0.158)	(0.158)	(0.197)
Non-routine abstract	0.159***	0.115**	0.0920*	0.124**	0.0637	0.353***	0.410***	0.341***	0.419***	0.296*
	(0.0484)	(0.0469)	(0.0471)	(0.0478)	(0.0454)	(0.114)	(0.135)	(0.129)	(0.149)	(0.156)
Routine	-0.272***	-0.183***	-0.191***	-0.159***	-0.180***	-0.581***	-0.449***	-0.471***	-0.396**	-0.459***
	(0.0688)	(0.0581)	(0.0558)	(0.0588)	(0.0587)	(0.161)	(0.169)	(0.161)	(0.178)	(0.173)
Non-routine manual	0.302***	0.219***	0.228***	0.205***	0.270***	0.272**	0.219*	0.275**	0.230*	0.363***
	(0.0597)	(0.0503)	(0.0502)	(0.0509)	(0.0530)	(0.112)	(0.119)	(0.108)	(0.119)	(0.111)
Img*Non-routine abstract	0.130	0.0460	0.144	0.0598	0.0749	-0.109	-0.0888	-0.0859	-0.262	-0.0480
	(0.0976)	(0.131)	(0.102)	(0.182)	(0.0768)	(0.220)	(0.276)	(0.250)	(0.304)	(0.303)
Img*Routine	-0.0642	-0.0424	0.0701	0.0667	0.0645	0.433*	0.809***	0.501*	0.812***	0.431
	(0.113)	(0.126)	(0.116)	(0.156)	(0.0844)	(0.251)	(0.279)	(0.270)	(0.276)	(0.326)
Img*Non-routine manual	0.0869	0.0787	-0.158	-0.110	-0.0773	-0.382*	-0.849***	-0.518**	-0.928***	-0.551*
	(0.117)	(0.142)	(0.107)	(0.181)	(0.0875)	(0.222)	(0.314)	(0.248)	(0.317)	(0.290)
Population composition constant										
within group	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
within and across group	NO	NO	YES	NO	YES	NO	NO	YES	NO	YES
Control for residence duration	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES
Observations	248	184	178	162	144	248	184	178	162	144
R-squared	0.530	0.621	0.845	0.767	0.687	0.190	0.212	0.205	0.266	0.124

Notes: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. In all regressions we control for an occupation specific labor demand shift index (see text for details). Regressions are weighted using the initial period employment level. In all columns, natives' wage residuals have been computed by including in the wage equation a full set of age*education dummies. In columns (1)-(3) and (6)-(8) immigrants' wage residuals have been computed by including in the wage equation a full set of age*education dummies and 27 country of birth dummies. In columns (4), (5), (9) and (10) wage residuals for immigrants have been computed by including a full set of dummies for age*educ*(residence duration) categories. In the weighting scenario Weight 1, population composition within occupations is kept constant as in the baseline for each nativity group. In the weighting scenario Weight 2, population composition within occupations is kept constant as that of natives in the baseline for both immigrants and natives. In columns (4), (5), (9) and (10) control for population composition effects includes immigrants' residence duration.

cupational average wages (*i.e.* between-occupation wage changes). This suggests that immigrants wage growth performance is not related to their specific skill endowment in performing some tasks. Conclusions are though modified when considering changes in returns to skills (*i.e.* within-occupation wage changes). Once composition effects have been controlled for (column 10), we find that in occupations requiring non-routine manual skills, immigrants wages have been compressing, while they have contributed to wage dispersion among natives. This pattern is likely to result from changes in skill endowments of immigrants and natives in non-routine manual occupations.[47] Indeed, we will show in the next section that immigrants' specialization in non routine manual tasks has decreased over the period (see also Figure 6). If this occurs within age and education groups, this may lead to wage compression in these occupations among immigrants.[48]

[47] Note that whether the initial skill endowment is the same or not for natives and immigrants, the negative and significant coefficient associated with the variable "Img· Non routine manual" (compared to the positive and significant coefficient associated with "Non routine manual") can only arise if there is a divergent change in the relative skill endowment of immigrants versus natives.

[48] To test the robustness of these results, we propose in Appendix D an alternative strategy, which consists in regressing the immigrant-native gaps in estimated between- and within-occupation components over the task indices:

$$\begin{aligned} \widehat{a_I} - \widehat{a_N} &= \tau_0 + \tau_1 \, \text{DemandShift}_j + \sum_{k=1}^{3} \tau_k TC_{jk}^{norm} + \mu_j \\ \widehat{b_I} - \widehat{b_N} &= \psi_0 + \psi_1 \, \text{DemandShift}_j + \sum_{k=1}^{3} \psi_k TC_{jk}^{norm} + \nu_j \end{aligned}$$

where TC_{jk} stands again for the task content measure within each occupation k = (1) non-routine abstract, (2) routine and (3) non-routine manual. Results in Table 8 in Appendix D are consistent with estimations presented in Table 1.

To summarize, when quantifying the "price effect" through a_j and b_j, Figure 9 suggests that immigrants' average wage growth across occupations has outperformed that of natives. This section qualifies the "price effect" and concludes that part of the more favorable wage dynamics of immigrants seems to be related to specific changes in their relative skill endowment. Next section analyzes the potential differences in occupational choices of immigrants and natives following incentives derived from the "price effect". We complement then the analysis of the "price effect" with an analysis of the "quantity effect". The intuition is that, if a "price effect" exists then it makes sense to explore whether immigrants are more likely to respond to these incentives than natives. We first relax the assumption of constant relative skill distribution within occupations over time and quantify the dynamics of occupational sorting for natives and immigrants depending on the "price effect" (measured by a_j and b_j) by occupation. In a second step, we qualify this "quantity effect" by relating immigrants' and natives' occupational sorting to the task content of occupations. We can then draw conclusions on changes in the relative skill endowments of natives and immigrants.

5.2 The quantity effect

Given the estimated changes in average wages and returns to skills (*i.e.* "price effect"), how immigrants' and natives' occupational choices have reacted to these incentives? Changes in average wages and returns to skills are likely to modify both individual's decisions on skill acquisition and on occupational choices. Different occupational choices between immigrants and natives, while facing an identical "price effect", will be suggestive of different changes in their respective skill endowments. The specific pattern of occupational sorting may explain immigrants' relatively higher wage growth across the occupational wage distribution. For instance, if they are moving from middle routine task-intensive occupations towards abstract task-intensive occupations at a higher pace than natives, this will drive up their relative wage growth.

To capture the differential pattern of occupational sorting between immigrants and natives, we first quantify the "quantity effect" by relating occupational choices to the two components of wage changes previously estimated for each occupation (*i.e.* between and within wage components of the "price effect"). This allows us to test whether immigrants and natives sort differently across occupations when facing identical wage changes. In other words, we compare the "quantity effect" across nativity groups. In a second step, we qualify the occupational sorting of immigrants and natives by relating occupational choices to the task content of occupations. We propose to conduct both analysis through the estimation of an occupational choice model.

Our occupational choice model, based on the conceptual framework presented in section 4, can be easily framed within a probabilistic or random utility choice model. For this, we suppose that when choosing their occupation, beside income potentials related to their relative skills endowment, individuals take into account some stochastic and idiosyncratic characteristics of occupations, which we assume are distributed independently of workers' skill endowments. Then, individuals choose from a variety of occupations their best option, taking into account income potential associated to each option and their specific characteristics. The indirect utility that a worker i derives from choosing an occupation j depends on her potential earning in the occupation, which we assume is a linear function of individual characteristics X_i, occupation-specific characteristics Z_j (occupation-specific returns to skills), and an idiosyncratic stochastic component:

$$U_{ij}^* = \rho_i X_i + \kappa_{ij} Z_j + \varepsilon_{ij} \tag{10}$$

An individual will choose among J occupations the one that provides the highest utility. We assume that the effects of occupation-specific characteristics on individual utility (κ_{ij}) vary across individuals, owing for instance to their specific skill endowments.[49] An individual will choose occupation j if $U_{ij}^* > U_{ik}^* \; \forall k \neq j$.

We define $U_{ij} = 1$ if individual i chooses occupation j and $U_{ij} = 0$ otherwise. Assuming that the disturbance term is iid and follows a Type-I extreme value distribution[50], we can estimate this random utility model using McFadden (1974)'s conditional logit:

$$\Pr(U_{ij} = 1) = \frac{\exp\{\rho_i X_i + \kappa_{ij} Z_j\}}{\sum\limits_{j=1}^{J} \exp\{\rho_i X_i + \kappa_{ij} Z_j\}} \tag{11}$$

Terms that do not vary across alternatives and are specific to the individual (*i.e.* X_i) are irrelevant and fall out of the probability. Therefore, we cannot estimate the effect of individual characteristics on the occupational choice (ρ) since they are invariant to the choice. However, we can estimate the effect on occupational choice of occupational characteristics (κ), and also their interactions with individual characteristics. To track the effect of changes in occupation-specific characteristics, we allow the effects to vary over time by interacting each characteristic with a dummy variable Year, equal to one in 2010-12. Therefore, we interpret the coefficients from a dynamic point of view, with respect to the base period (1994-1996). Coefficients associated with these interaction terms capture the change relatively to the base period in the probability of choosing an occupation relatively to its characteristics.

5.2.1 Measuring the "quantity effect": occupational choices in case of wage change

Let us first start estimating the pure "quantity effect", which relates the occupational choice to the between- and within-occupation components of the "price effect". In Figure 10, the left-hand (right-hand) side panel displays on the X-axis the 10th, 25th, 50th, 75th and 90th percentiles of the distribution of the between- (within-) component of wage changes.[51] The Y-axis represents the variation in the probability of choosing an occupation located at the corresponding percentile of the

[49] In this setting, X_i can be thought as the vector of individual skill endowments and Z_j as a vector denoting the sensitivity of the occupation to each skill component of κ_{ij}.

[50] We should invoke here the independence of irrelevant alternatives (IAA) assumption. Choices are then independent from irrelevant alternatives and therefore the omission of a choice does not significantly alter estimates.

[51] The between- and within-occupation components we consider here are those estimated on the sample of natives while removing age-education composition effects.

specific component of wage changes with respect to the base period 1994-1996. In other words, it is the marginal effect associated with the corresponding percentile in the distribution of the between- (or within-) component relative to the marginal effect in the base period. An upward profile along the distribution of the between- (within-) occupation component indicates that occupations where the average wage (wage dispersion) has relatively increased by more, are more likely to be chosen over time (*i.e.* are more likely to be chosen in period 2010-2012 than they were in period 1994-1996). In contrast, a downward probability choice profile indicates that occupations in which the corresponding component has increased relatively more are less likely to be chosen over time. The interpretation of results in Figure 10 must then be focused on the slope of the curve and not the associated absolute values of the marginal effects which are actually defined in relative terms.

The solid curves represent the results for the observed population sample, *i.e.* without controlling for composition effects related to age, education and residence duration. The dashed curves represent the results with a reweighted sample representing a constant population composition over time and across nativity groups (*i.e.* same age-education composition in both periods for immigrants and natives and same residence duration for immigrants in both periods). To precisely evaluate the importance of the "quantity effect" as a driver of the differential wage dynamics between natives and immigrants, we need to eliminate the mechanical composition effects. Estimation results based on the reweighted sample allow then to isolate the contribution of the "quantity effect" (*i.e.* occupational sorting following the "price effect" incentives) to the wage dynamics.

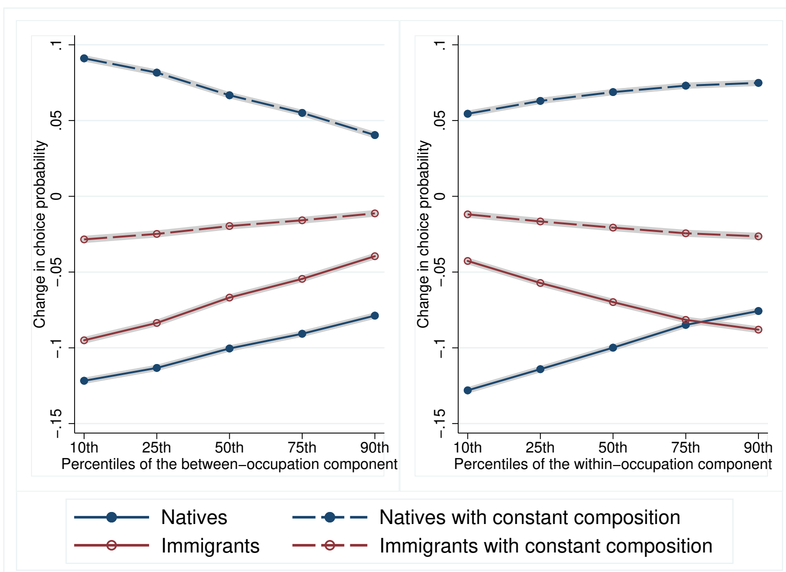
The left-hand side panel of Figure 10 reveals a positive sorting: occupations with higher average wage growth are increasingly likely to be chosen by both immigrants and natives. Though, sorting of natives in such occupations is entirely driven by their skill upgrading in terms of age and education. When removing composition effects, we find instead that the probability of natives to choose occupations with higher wage growth has decreased between 1994-1996 (*i.e.* base period) and 2010-2012. In contrast, at similar and constant population composition, immigrants are more likely to choose such occupations in 2010-2012 than in 1994-1996.

In the right-hand side panel of Figure 10, we observe that while natives are more likely in period 2010-2012 to choose occupations with a greater rise in wage dispersion, immigrants are less likely. This pattern remains (but is clearly smoothed) once population composition effects have been controlled. Immigrants are slightly less likely to choose occupations whose wage dispersion has increased relatively more, while natives are more likely to choose them. Overall, immigrants' and natives' occupational choices have differed in spite of facing identical changes in returns to skills.

5.2.2 Qualifying the "quantity effect": the role of tasks

Next we qualify the differential sorting of natives and immigrants by relating the occupational choice to the task content of occupations. These different occupational choices (would) result from different changes in comparative advantages across nativity groups, which are related to different changes

Figure 10: Change in the probability of choosing an occupation depending on the wage changes between 1994-1996 and 2010-2012



Notes: The X-axis stands for the 10th, 25th, 50th, 75th and 90th percentiles of the between-occupation coefficient distribution for the left-hand side panel and of the within-occupation coefficient distribution for the right-hand side panel. The between- and within-occupation components we consider here are those estimated from equation (6) on the sample of natives while removing age-education composition effects. In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change from period 1 to period 2 in the probability of choosing an occupation located at the corresponding percentile of the distribution of the between-occupation or within-occupation coefficients. The shadowed area corresponds to the 95% confidence interval.

in their skill endowment.[52] To take into account variations across occupations in the probability to be exposed to a minimum wage change, we also control for the share of minimum wage earners in occupations. Immigrants and natives may be differentially attracted by occupations whose wage changes are tightly related to minimum wage changes if, owing to some specific characteristics, they have different propensities to be minimum wage earners. This feature is particularly relevant in the French context where the minimum wage level has experienced a sharp increase over the period. Although we control for the effects of minimum wage changes to produce the different estimates reported below, we report the results specifically related to this feature in Section 6, where we analyze in more detail how minimum wage changes have altered the "price effect" and the "quantity effect".

We again interact occupational characteristics represented by task's intensity indices with a period dummy (Year) to capture the dynamics of occupational choices with respect to the base period (1994-1996). Coefficients associated with the interaction terms (Year $\times$ Task$_j$) capture the change relatively to the base period in the probability of choosing an occupation which is relatively more intensive in a specific task (*i.e.* we condition on the value for all the other tasks).[53]

Figures 11, 12 and 13 display on the X-axis the 10th, 25th, 50th, 75th and 90th percentiles of the intensity index distribution for a particular task and on the Y-axis the variation in the probability of choosing an occupation located at the corresponding percentile of this specific task dimension. These graphs portray the time pattern of occupational sorting of immigrants and natives along each task intensity distribution. An upward profile in Figures 11, 12 and 13, along the task intensity index distribution indicates that occupations relatively more intensive in the corresponding task are increasingly likely to be chosen over time. Alternatively, a downward probability choice profile indicates that occupations relatively more intensive in the corresponding task are less likely to be chosen over time. These graphs show the type of tasks in which immigrants and natives are increasingly concentrated and therefore reveal how the pattern of their comparative advantages has evolved over time. Again, solid curves represent the results for the observed population sample while dashed curves consider a constant population composition over time and across nativity groups (in terms of age-education-residence duration). This later effect will reveal whether differences in occupational mobility are due to genuine different comparative advantages within age*education skill groups or occur due to standard differences in observable age*education characteristics.[54]

Figure 11 displays the predicted change (from 1994-1996 to 2010-2012) in the conditional choice

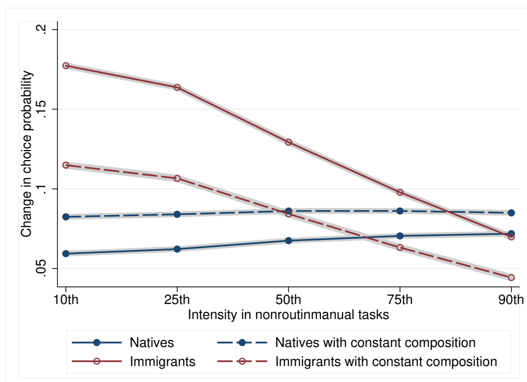
[52]Our approach is similar to that adopted in the microeconomic literature on revealed preferences. Taking as given changes in returns to skills, we infer about immigrants' and natives' changes in relative skill endowment by looking at their differential reaction to changes in the pricing of skills. Our approach is also related to that of Basso, Peri, and Rahman (2017), who working with US data provide a descriptive analysis of the evolution in the supply of analytical, routine and manual tasks by immigrants and natives inferred from their distribution among occupations along time. In our case, we estimate occupational choices driven by changes in average wages and returns to skills. Moreover, we focus on the variation in the probability of choosing a job in 2010-2012 with respect to 1994-1996 given this price incentives.

[53]The effect of the minimum wage is controlled by introducing the term Year $\times$ Sharew$_j^{min}$ which captures the change relatively to the base period in the probability of choosing an occupation with a relatively larger share of minimum wage earners.

[54]For instance, the fact that more educated workers may have comparative advantage in less routine occupations.

probability of an occupation along the distribution of the non-routine manual task index. The probability that immigrants choose an occupation which is relatively more intensive in non-routine manual tasks has declined over time. Instead, natives show a weakly increasing pattern in their probability to choose occupations which are relatively more non-routine manual intensive. Controlling for changes and differences in population composition in terms of age-education-residence duration does not affect these patterns. Therefore, relatively to natives, immigrants are loosing comparative advantage in non-routine manual tasks. Immigrants seem to have moved away from non-routine manual occupations. This pattern of mobility is consistent with the decreasing wage dispersion estimated for immigrants in Table 1 (column 10) in occupations requiring non-manual skills.[55]

Figure 11: Change in the probability of choosing an occupation depending on the intensity of non-routine manual tasks



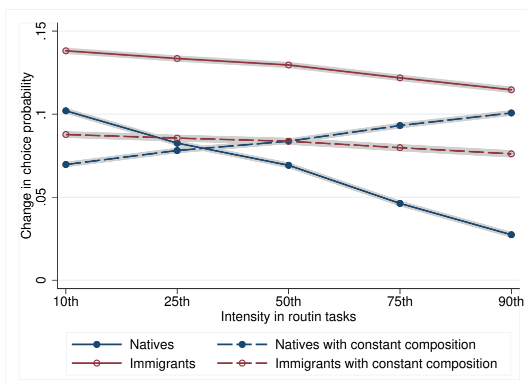
Notes: The X-axis stands for the 10th, 25th, 50th, 75th and 90th percentiles of the non-routine manual task intensity index distribution. The task percentiles have been computed over the natives occupational employment distribution in the baseline (1994-1996). In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change from period 1 to period 2 in the probability of choosing an occupation located at the corresponding percentile of the task intensity index. The shadowed area corresponds to the 95% confidence interval.

Figure 12 displays changes in the probability to choose an occupation depending on its intensity in routine tasks. Natives' comparative advantage in routine tasks clearly declines over time: the probability for a native to choose an occupation located at the first decile of the routine index has increased by a factor of three relatively to an occupation located in the upper decile. Natives seem therefore to be moving away from routine task-intensive occupations. This is also the case for immigrants but to a much lower extent. Therefore, immigrants seem to be gaining comparative advantage relatively to natives in these more routine occupations. The pattern and the difference across nativity groups are though explained by changes and differences in the composition of the populations. At constant and identical population composition (in terms of age-education-residence

[55]Unlike our findings Basso, Peri, and Rahman (2017) show that in the US since 1980 immigrants have become relatively more concentrated in non-routine manual tasks than natives. The later have become rather concentrated in non-routine analytical tasks. These differences with respect to our findings may be due to both differences in the composition of the pool of immigrants in France and the US (in terms of qualification, origin countries, residence duration or age), and, on the demand side, differences in the dynamics of the occupational structure in France and the US.

duration), we find instead that relatively to immigrants, natives are more likely to choose routine occupations. Therefore, at similar characteristics, natives have gained comparative advantage in these occupations. Combined with Figure 11, this suggests that, despite their departure from non-routine manual task-intensive occupations, immigrants do not seem to be flowing towards routine task-intensive occupations. This is consistent with estimations in Figure 10. Over the past decades immigrants have increasingly allocated towards occupations experiencing high average wage growth. Recent technological changes have promoted a relative decrease in the price of routine intensive goods (see Autor, Levy, and Murnane (2003), Autor, Levy, and Kearney (2006), Goos and Manning (2007), Spitz-Oener (2006) or Maurin and Thesmar (2004)) implying a reduced average wage growth in occupations intensive in routine tasks. Immigrants have thus flied out from this type of occupations.

Figure 12: Change in the probability of choosing an occupation depending on the intensity of routine tasks

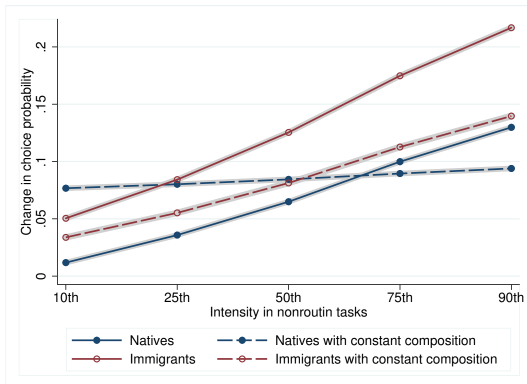


Notes: The X-axis stands for the 10th, 25th, 50th, 75th and 90th percentiles of the non-routine manual task intensity index distribution. The task percentiles have been computed over the natives occupational employment distribution in the baseline (1994-1996). In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change from period 1 to period 2 in the probability of choosing an occupation located at the corresponding percentile of the task intensity index. The shadowed area corresponds to the 95% confidence interval.

Figure 13 displays the predicted change in the probability of choosing an occupation depending on its relative intensity in non-routine abstract tasks. Occupations which are more intensive in non-routine abstract tasks are increasingly likely to be chosen by both immigrants and natives. Though, this greater specialization of natives in non-routine occupations is entirely due to their skill upgrading in terms of age and education. When removing age-education-residence duration composition effects, we find that the probability of natives to choose occupations more intensive in non-routine tasks has only slightly increased. In contrast, at similar and constant population composition, we observe a greater specialization of immigrants in non-routine abstract task-intensive occupations. Therefore, relatively to natives, immigrants seem to have gained comparative advantage in non-routine abstract task-intensive occupations.[56]

[56]This result is particularly interesting since it is in clear contrast with findings of other papers dealing with migration in the US (see Peri and Sparber (2011b), Peri and Sparber (2011a), Peri and Sparber (2009), D'Amuri and Peri. (2014)) or Basso, Peri, and Rahman (2017).

Figure 13: Change in the probability of choosing an occupation depending on the intensity of non-routine tasks



Notes: The X-axis stands for the 10th, 25th, 50th, 75th and 90th percentiles of the non-routine abstract task intensity index distribution. The task percentiles have been computed over the natives occupational employment distribution in the baseline (1994-1996). In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change from period 1 to period 2 in the probability of choosing an occupation located at the corresponding percentile of the task intensity index. The shadowed area corresponds to the 95% confidence interval.

Combining Figures 10, 11, 12 and 13 portrays an immigrant population that has experienced an upward occupational mobility relatively to natives and has allocated towards occupations whose average wage has increased the most. Between 1994-96 and 2010-12, immigrants are upgrading from the bottom (manual tasks) to the upper part of the wage distribution (non-routine abstract tasks).

6 Robustness checks: minimum wage effects

Unlike many developed countries, the minimum wage in France has increased at a higher pace than the average wage. Moreover, around 11% of workers are minimum wage earners, which is one of the highest shares in OECD countries. Therefore, minimum wage changes in France are expected to have an impact on wage levels, wage distribution, and employment. Minimum wage changes can impact both the "price effect", by increasing returns to skills which are traditionally employed at the bottom of the wage distribution, and the "quantity effect", by promoting sorting towards occupations with a high share of minimum wage earners. We report below the estimates when taking into account the potential effect of minimum wage changes on these two effects.

6.1 Minimum wage changes and the price effect

To gauge how minimum wage changes may impact our estimates of the "price effect", we propose to concentrate on a set of workers that are the least likely to be affected by minimum wage changes: those earning above 1.2 times the minimum wage. We proceed as follows. First, we identify the characteristics of this set of workers in the baseline period 1994-1996. Second, we fix the population-composition of each occupation in period 2010-2012 to be the same as that of the sub-sample of

Table 2: Task contribution net of the minimum wage to between- and within-occupation wage changes, from 1994-96 to 2010-12. Natives vs. Immigrants.

Dependent variables: Between- and within-occupation wage changes

	Between-occupation wage change				Within-occupation wage change			
Scenarios	Weight 1	Weight 2	Weight 1	Weight 2	Weight 1	Weight 2	Weight 1	Weight 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrant	0.316***	0.479***	0.278***	0.123*	0.330**	0.494**	0.641***	0.142
	(0.0859)	(0.0721)	(0.0736)	(0.0665)	(0.153)	(0.211)	(0.147)	(0.140)
Non-routine analytical-interactive	0.214***	0.214***	0.168**	0.120*	0.511***	0.476***	0.419***	0.323***
	(0.0637)	(0.0687)	(0.0682)	(0.0637)	(0.126)	(0.130)	(0.115)	(0.119)
Routine manual-cognitive	-0.310***	-0.336***	-0.293***	-0.309***	-0.578***	-0.552***	-0.478***	-0.471***
	(0.0860)	(0.0905)	(0.0853)	(0.0898)	(0.150)	(0.151)	(0.133)	(0.141)
Non-routine manual	0.338***	0.353***	0.331***	0.385***	0.327**	0.338***	0.279***	0.344***
	(0.0764)	(0.0794)	(0.0754)	(0.0777)	(0.125)	(0.121)	(0.101)	(0.0966)
Img*Non-routine analytical-interactive	0.0337	0.0400	0.113	0.0465	-0.271	-0.300	-0.318	-0.244
	(0.144)	(0.174)	(0.190)	(0.0964)	(0.250)	(0.367)	(0.278)	(0.276)
Img*Routine manual-cognitive	0.276	0.192	0.197	0.122	0.311	0.515*	0.922***	0.800**
	(0.195)	(0.177)	(0.175)	(0.127)	(0.272)	(0.291)	(0.255)	(0.322)
Img*Non-routine manual	-0.254	-0.357**	-0.324*	-0.139	-0.398	-0.665*	-0.887***	-0.669**
	(0.174)	(0.174)	(0.186)	(0.117)	(0.293)	(0.383)	(0.301)	(0.333)
Population composition constant								
within group	YES	YES	YES	YES	YES	YES	YES	YES
within and across group	NO	YES	NO	YES	NO	YES	NO	YES
Control for residence duration	NO	NO	YES	YES	NO	NO	YES	YES
Observations	158	148	152	136	158	148	152	136
R-squared	0.615	0.681	0.513	0.417	0.265	0.304	0.546	0.186

Notes: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. In all regressions we control for an occupation specific labor demand shift index (see text for details). Regressions are weighted using the initial period employment level. In all columns, natives' wage residuals have been computed by including in the wage equation a full set of age*education dummies. In columns (1)-(3) and (6)-(8) immigrants' wage residuals have been computed by including in the wage equation a full set of age*education dummies and 27 country of birth dummies. In columns (4), (5), (9) and (10) wage residuals for immigrants have been computed by including a full set of dummies for age*educ*(residence duration) categories. In the weighting scenario Weight 1, population composition within occupations is kept constant as in the baseline for each nativity group. In the weighting scenario Weight 2, population composition within occupations is kept constant as that of natives in the baseline for both immigrants and natives. In columns (4), (5), (9) and (10) control for population composition effects includes immigrants' residence duration.

workers in that occupation earning above 1.2 times the minimum wage in the baseline period 1994-1996. That is, for every occupation and both periods, we focus on a constant population-composition which is representative of workers for which we think minimum wage changes are less likely to bind.

Results for this particular sample are summarized in Table 2.[57] As revealed by Table 9 in Appendix D, considering workers outside the reach of minimum wage decreases by more than a half the estimated immigrants' occupational wage growth premium. Minimum wage changes therefore have significantly contributed to immigrants' better relative wage performance. Interestingly, wage growth among this sub-sample of better paid workers is explained by their more favorable skill returns (see column 8), *i.e.* by wage changes within occupations. In Table 2, we control for the task content of occupations, while allowing for heterogenous returns between immigrants and natives. Consistently with estimates in Table 1, we find that there are immigrant-specific positive returns to skills associated with routine tasks and negative returns to skills associated with non-routine manual tasks. Overall, these changes in returns to skills are rather consistent with a change in skill endowment promoting immigrants' upward occupational mobility. As we show in Table 1, differences between immigrants and natives in average wage growth across occupations are not due

[57] We do not present here results of the Baseline scenario since they would be identical to columns (1) and (6) from Table 6. Indeed the Baseline scenario does not use counterfactual weights.

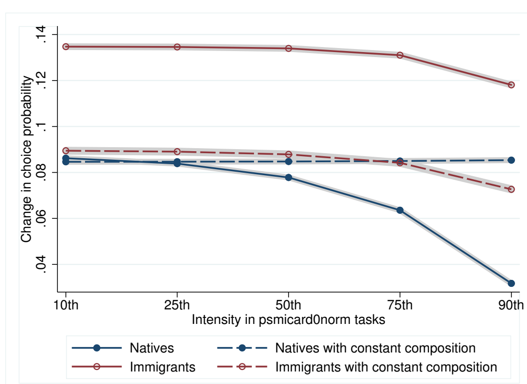
to differences in returns to skills.

6.2 Minimum wage changes and the quantity effect

Minimum wage changes also affect workers' sorting across occupations, that is, what we have called, the "quantity effect". In Figure 14, we display a graph which is similar to ones in section 5.2 but which considers the share of minimum wage earners in the occupation. Therefore, Figure 14 shows the pattern of sorting across occupations that are increasingly likely to be affected by minimum wage changes over the period. The figure reveals that the probability of choosing occupations more exposed to minimum wage changes has decreased over time for both immigrants and natives. However, when removing composition effects, we find that this decline is only effective among immigrants at the top of the distribution (*i.e.* for occupations very exposed to minimum wage changes) while the choice probability has remained essentially constant among natives. Therefore, relatively to natives, immigrants are becoming less concentrated in occupations being the most exposed to minimum wage changes.

We conclude that selective sorting of immigrants towards occupations highly exposed to minimum wage changes is unlikely to have had an important impact on the overall relative good wage performance of immigrants.[58] Instead, this performance seems to be better explained by changes in comparative advantages leading to upward occupational wage mobility towards occupations which have actually benefitted from the highest average wage growth and whose returns to skill are high (non-routine abstract occupations).

Figure 14: Change in the probability of choosing an occupation depending on the share of minimum wage earners in the baseline (1994-1996)



Notes: The X-axis stands for the 10th, 25th, 50th, 75th and 90th percentiles of the distribution of the share of minimum wage earners across occupations. The minimum wage share have been computed over the wage distribution of natives within each occupations in the baseline. The value of the percentiles across occupations have been computed over the natives occupational employment in the baseline. In the Y-axis, using the conditional logit estimates we report the predicted change from period 1 to period 2 in the probability of choosing an occupation located at the corresponding percentile in the distribution of the share of minimum wage earners across occupation. The shadowed area corresponds to the 95% confidence interval.

[58] This does not mean that the minimum wage has had no impact.

Combining the results in Table 2 with those in Figure 14 and those in section 5.2, we conclude that immigrants' favorable wage dynamics is, at least, explained by two important factors. On the one hand, we find that immigrants have moved upward across the occupational wage ladder between 1994-1996 and 2010-2012. On the other hand, we find that part of immigrants' more favorable wage growth has been driven by minimum wage increases over the period.[59] This result also suggests that wage growth premium of less and more skilled immigrants are explained by different factors. For the least skilled, changes in skill prices brought about by minimum wage changes are probably the dominant factor. In contrast, changes in relative skill endowments and occupational sorting are the main factor among more skilled immigrants.

7 Conclusion

Using the French Labor Force Survey, the EurOccupations and O*NET datasets, we analyze two crucial sources of immigrants' labor market performance: immigrants' skills and how these skills are valued. Despite being non-observable, we have been able to assess changes in immigrants' and natives' relative skill endowments along dimensions that have so far been overlooked in the literature. These endowments are related to task specific returns to skills.

We show that in France immigrants' wage growth has outperformed that of natives along the whole wage distribution, over the period 1994-2012. While a substantial part of immigrants' wage growth is due to their specific characteristics, we show that immigrants have also accumulated skills which are more rewarded along the occupational wage ladder. In particular, their pattern of occupational sorting over the period suggests that they have moved upward in the occupational wage distribution towards high wage growth occupations at a higher pace than natives.

In addition, we identify variations in the sources of the immigrant-native wage growth premium depending on the skill level. While the premium for the most skilled immigrants results from their increasing specialization in more rewarded tasks, the wage growth performance of the least skilled immigrants seems to be mainly related to the sharp increases in the French minimum wage over the period.

Though not unequivocal, our results show that the relative "labor market quality" of immigrants has improved over the last two decades in France. Interestingly, this improvement is not only the consequence of changes in the market reward of skills but potentially also the result of immigrants' human capital adjustment. Overall, it seems that immigrants have been able to better price their skills by moving across tasks. We hope to confirm these patterns in future research by investigating, using individual panel data, the dynamics of wages and human capital adjustments following changes in skills and tasks driven by globalization and technological changes. In addition, while this paper focuses on male earnings, bringing into the analysis gender differences will be a worthy complement to the present research.

[59] One issue we do not deal with is the effect of minimum wage on mobility into non-employment.

Appendices

A Databases

A.1 Sample Characteristics

Table 3: Sample characteristics per year, French LFS 1993-2012.

	N	% Immigrants	Age immigrant	Age native	Education immigrant	Education native	Wage immigrant	Wage native	Residence duration
1994	40059	11.23	41.04	37.34	1.51	1.56	1542.84	1597.94	19.12
1995	40814	11.39	41.05	37.46	1.53	1.59	1389.61	1308.82	18.66
1996	41186	11.41	41.43	37.63	1.59	1.60	1539.49	1341.79	18.94
1997	40505	11.31	41.66	37.86	1.60	1.64	1211.57	1322.40	19.30
1998	41070	11.03	41.73	37.94	1.59	1.66	1217.72	1234.47	19.46
1999	41969	11.23	42.11	37.94	1.62	1.69	1282.79	1239.60	19.83
2000	35922	10.66	41.95	37.84	1.68	1.71	1261.94	1297.84	21.87
2001	43525	11.33	42.51	38.02	1.66	1.75	1342.89	1356.46	19.33
2002	43287	10.82	42.53	38.22	1.69	1.78	1292.65	1299.52	19.28
2003	25950	10.52	42.43	38.22	1.77	1.84	1454.25	1513.18	25.41
2004	24694	10.74	41.96	37.97	1.83	1.90	1496.39	1509.01	25.05
2005	26256	10.36	42.34	38.46	1.89	1.92	1430.54	1498.26	25.26
2006	26068	10.55	42.60	38.64	1.88	1.93	1431.43	1501.69	25.51
2007	27423	10.99	42.43	38.69	1.89	1.97	1401.80	1519.42	25.13
2008	27995	11.57	42.49	38.79	1.93	2.01	1448.50	1509.25	24.52
2009	32348	11.39	42.75	39.24	1.97	2.03	1465.90	1559.08	24.78
2010	37169	11.51	42.66	39.59	1.96	2.06	1477.09	1557.79	24.44
2011	39598	11.36	43.10	39.75	2.00	2.09	1502.33	1566.87	24.87
2012	39553	11.54	43.21	40.36	2.03	2.11	1525.00	1567.49	24.48

Notes: French Labour Force Survey 1993-2012. Individuals in the private sector declaring an strictly positive wage. Education: "1: Less than secondary education, 2: Secondary education, 3: Baccalaureate+2 years, 4: University studies". Real wages in euros. For the period 1994-2002 there are only 11,187 immigrants for which the date of entry in France is known while this number raises to 77,316 immigrants for the period 2003-2012. This is likely to be responsible for the break in the residence duration observed from 2003.

Table 4: Population composition by nativity groups, French LFS 1993-2012.

	Frequency	Population composition in percent
French	635.277	89.41%
North African	26.842	3.78%
African	9.291	1.31%
South-Eastern Asian	3.083	0.43%
South-European	20.609	2.90%
North-Europeans	6.984	0.98%
East-Europe and Russia	5.334	0.75%
South-American	1.561	0.22%
North American	264	0.04%
Turk	1.287	0.18%
Total	710.532	100.00

Notes: French Labour Force Survey 1993-2012. Individuals in the private sector declaring an strictly positive wage. There are 4374 observations for which the origin is unknown.

A.2 Occupational task composition

Table 5: Occupational tasks.

Non-routine Analytical	Organizing, Planning, and Prioritizing Work ; Getting Information ; Analyzing Data or information; Making Decisions and Solving Problems ; Developing Objectives ; Judging the Qualities of Things, Services, or People ; Updating and Using Relevant Knowledge ; Interacting with Computers ; Thinking Creatively ; Estimating the Quantifiable Characteristics of Products, Events, or Information ; Evaluating Information to Determine Compliance with Standards; Scheduling Work and Activities ; Interpreting the Meaning of Information for Others ; Processing Information and Strategies.
Non-routine inter-personal	Guiding, Directing, and Motivating Subordinates ; Communicating with Supervisors, Peers, or Subordinates ; Communicating with Persons Outside the Organization ; Developing and Building Teams ; Resolving Conflicts and Negotiating with Others ; Performing for or Working Directly with the Public ; Staffing Organizational Units Providing Consultation and Advice to Others ; Coordinating the Work and Activities of Others ; Selling or Influencing Others ; Training and Teaching Others ; Assisting and Caring for Others ; Coaching and Developing Others ; Establishing and Maintaining Interpersonal Relationships ; Monitoring and Controlling Resources.
Routine Cognitive	Performing Administrative Activities, Documenting/Recording Information.
Routine Manual	Handling and Moving Objects ; Performing General Physical Activities ; Repairing and Maintaining Mechanical Equipment ; Repairing and Maintaining Electronic Equipment.
Non-routine Manual	Operating Vehicles, Mechanized Devices, or Equipment ; Inspecting Equipment, Structures, or Material ; Monitoring Processes, Materials, or Surroundings ; Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment.

Source : Constructed using data from O*NET.

B Removing composition effects in wage changes

In order to capture the precise contribution of tasks to the estimated residual wage differentials between 1994-1996 and 2010-2012, we remove the part of the residual wage change that results from changes in the composition of occupations in terms of age, education and residence duration. We propose alternative scenarios where we successively impose occupations to keep the same composition in terms of workers' age-education-residence duration in both periods, for each nativity group separately or taking as reference natives.

B.1 A cell-by-cell approach

We rely on the cell-by-cell approach suggested by Lemieux (2002), which is equivalent to the reweighting method of DiNardo, Fortin, and Lemieux (1996) but has the advantage to be more flexible. This non-parametric procedure consists first of dividing the data into a limited number C of cells, in each occupation j and at each period t, according to a set of dummy variables $x_{ijt} = (x_{i1jt}, \dots, x_{icjt}, \dots x_{iCjt})$. This procedure is based on the definition of the same age-education cells for natives and the same age-education-residence duration cells for immigrants within each of the occupations. We keep only cells that are observed in both periods to ensure we have a common support when applying this reweighting method.

For both native and immigrant workers, we use the following dummies to define age-education cells: we consider 9 distinct 5-year interval age groups (from 15 to 60), and within each age group we distinguish 4 education degrees (below baccalaureate, baccalaureate or equivalent, baccalaureate+2 years, higher degree). For immigrant workers, we additionally distinguish within each age-education cells two residence durations: less than 10 years, 10 years and more. Thus, we can define up to 36 age-education cells for natives and up to 72 age-education-residence duration cells for immigrants. Age is often used to proxy actual work experience in the literature. We could also use instead potential work experience, which is, under the standard assumption, equal to the worker's age minus the typical age at which she is expected to have completed her education.[60] A caveat of using such proxies is that actual work experience is measured with error, except for individuals who work full-time and continuously. Indeed, when work experience is acquired without interruption after schooling, potential experience and actual experience coincide. In contrast, potential experience may be a noisy proxy of actual experience for women or immigrants (see, *e.g.* , Barth, Bratsberg, and O.Raaum (2012)).

For each cell c, in occupation j and at period t, we then estimate a reweighting factor Ψ_{cjt} that will be used to calculate a counterfactual sample weight : $\omega^a_{cjt} = \Psi_{cjt}\,\omega_{cjt}$, where ω_{cjt} is the original

[60] Borjas (2003) assumes that the age of entry in the labor force is 16 for high school dropouts with no vocational education, 19 for high school dropouts with vocational education or high school graduates without vocational education, 21 for high school graduates with vocational education, 24 for those who completed non-university higher education and 25 for workers who hold a university degree. Ottaviano and Peri (2012) calculate years of potential experience under the assumption that people without a high school degree enter the labor force at age 17, people with a high school degree enter at 19, people with some college enter at 21, and people with a college degree enter at 23.

sample weight of cell c, in occupation j and period t. The reweighting factor of each cell c is built up first from the sample share of workers in the cell (natives or immigrants), in occupation j and period t, denoted η_{cjt}, which is given by the sample average of the dummy variable x_{ict}:

$$\bar{x}_{cjt} = \sum_{i} \omega_{it}\, x_{icjt} = \sum_{x_{icjt}} \omega_{it} = \eta_{cjt}, \tag{12}$$

where ω_{it} is the original LFS sample weight, that we have multiplied by monthly hours of work, following for instance DiNardo, Fortin, and Lemieux (1996), and Lemieux (2002).

To insure that the age-education-years of residence composition is the same for each occupation in periods 0 and 1, we assign to each cell c the same average weight of the cell at period 0. This implies including the sample share of cell c in period 0 in the calculation of the corresponding reweighting factors. Thus, the reweighting factor of cell c in occupation j and period t is defined as:

$$\Psi_{cjt} = \frac{\eta_{c0}}{\eta_{cjt}}, \tag{13}$$

where η_{cjt} corresponds to the observed share of cell c (defined by a particular age-education-residence duration) in occupation j in period t, and η_{c0} is the same share in period 0. That is, the numerator stands for the counterfactual sample share of cell c in occupation j that we want to impose to be identical for both periods.

The resulting counterfactual sample weights $\omega^{a}_{cjt} = \Psi_{cjt}\, \omega_{cjt}$ allow to estimate the individual wage distribution that would have arisen if the age-education composition for natives and age-education-residence duration composition for immigrants in each occupations had been constant over time.

B.2 The alternative scenarios

We propose to measure the contribution of tasks' returns to between- and within-occupation wage changes under five alternative scenarios differing on (i) the explanatory variables considered to estimate residual wages with the Mincer equation, and (ii) the sampling weights employed to estimate occupation-specific residual wage deciles used in the regression and to compute the between and within components. The 5 scenarios are:

- The "Baseline" scenario corresponds to the case where residual wages result from regressing the log wage over standard variables in a Mincer equation, age $\times$ educ, and the country of origin. Then, occupation-specific residual wage deciles are estimated using the LFS sampling weights.

- In the "Composition 1 (Weight 1 type)" scenario, estimated residual wage deciles are obtained as in the Baseline scenario, and they are reweighted to insure a constant age-education composition by nativity group within occupations.

- The “Composition 2 (Weight 2 type)” scenario differs from the previous one in that the reweighting factor imposes the age-education composition of natives in period 0, for both natives and immigrants in periods 0 and 1. This scenario is useful for interpreting differences between immigrants and natives.
- In the “Residence 1 (Weight 1 type) ” scenario, residual wages for immigrants are obtained by regressing the log wage over age $\times$ educ $\times$ resid[61] and the origin country. Residual wage deciles are then obtained using counterfactual weights insuring a constant composition of worker characteristics (age $\times$ educ $\times$ resid) by nativity group within occupations.
- In the “Residence 2 (Weight 2 type)” scenario, residual wage deciles are obtained using counterfactual weights insuring a constant composition of worker characteristics (age $\times$ educ $\times$ resid) across nativity groups within occupations: the age-education composition of natives in period 0 is taken as reference.

[61] The resid variable is defined for more than ten years of residence or less than ten years of residence.

C Figures

C.1 Variance decomposition analysis

To assess the driving role of occupations in the dynamics of the wage differentials between individuals, we propose a wage variance decomposition analysis for each nativity group. We first remove for each nativity group the part of total wage variance ("Total" line) which is due to observable individual characteristics by considering the residual wage variance ("Residual" line), *i.e.* the variance of residuals from the following wage equation :

$$\ln w_{int} = \alpha_{nt} + \beta_{nt}\,\text{age} \times \text{educ} \times \text{resid}_{int} + \gamma_{nct}\,\text{country}_{inct} + \tilde{w}_{int},$$

where w_{int} stands for the hourly wage of an individual i from nativity group n (natives, immigrants) in year t, age $\times$ educ $\times$ resid_{int} stands for the different individual cells (up to 72 for immigrants and 36 for natives) we define each year from the following groups : 9 age groups (from 15 to 60 years old using five-year intervals), 4 educational groups (less than Baccalaureate, Baccalaureate or equivalent, Baccalaureate plus two years, and higher degrees) and 2 levels for the residence duration (less than 10 years, more than 10 years). country_{inct} contains a set of dummy variables for geographical origins of immigrants (a dummy for each of the 27 countries distinguished in the LFS). $\tilde{w}_{int}$ are the estimated residual wages, that we then decompose into between- and within-occupation components by relating them to a full set of occupation dummies as follows :

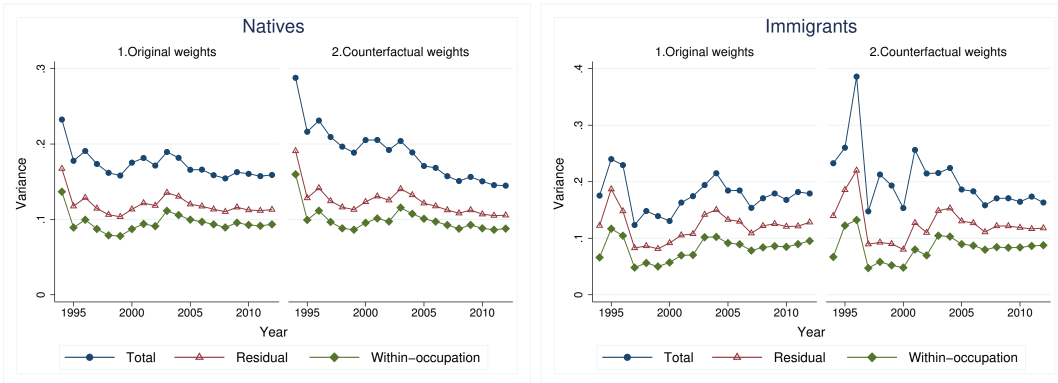
$$\tilde{w}_{int} = \theta_{njt}\,\text{occupation}_{injt} + \nu_{int},$$

where occupation_{injt} stands for the j-th occupational dummy variable. ν_{int} is the part of the first-stage wage residual that is not explained by differences across occupations but rather by unobserved differences across individuals working in the same occupations (*i.e.* skill endowments, skill returns, unobserved abilities or reservation wages). The within-occupation residual wage variance ("Within-occupation" line) is obtained by computing for each year and for each nativity group the variance of ν_i, and represents the part of residual wage variance that is explained by wage disparities within occupations. Thus, the vertical distance between the residual wage variance and the within-occupation residual wage variance corresponds to the part of residual wage variance that is explained by differences between occupations, *e.g.* different task content and occupation-specific skill returns. In contrast, the vertical distance between the x-axis and the within-occupation residual wage variance corresponds to the part of the residual wage variance explained by differences across individuals employed in the same occupation.

Wage differences within and between occupations keep a major place in total wage variance even once we remove the mechanical effect coming from changes in the composition of observable characteristics on residual wages (*i.e.* composition effects), by reweighting each nativity sample so as to get the same composition in terms of age, education and residence duration[62] (see "Counter-

[62] As explained in appendix B, we reweight our sample by $\omega^a_{ct} = \Psi_{ct}\,\omega_{ct}$, where ω_{ct} is the original sample weight of

Figure 15: Variance decomposition analysis by nativity group. France 1994-2012



Notes: The vertical distance between the Total line and the Residual line corresponds to wage disparities explained by age, education, residence duration and origin country differences. The vertical distance between the Residual line and the Within-occupation line corresponds to the part of the residual wage variance that is explained by differences between occupations. The vertical distance between the X-axis and the Within-occupation line corresponds to the part of residual wage variance that is explained by wage disparities within occupations. In the panels "Original weights" we use the sample weights provided by the LFS. In the panels "Counterfactual weights" we reweight each nativity group so that the age-education-years of residence composition is constant over all years.

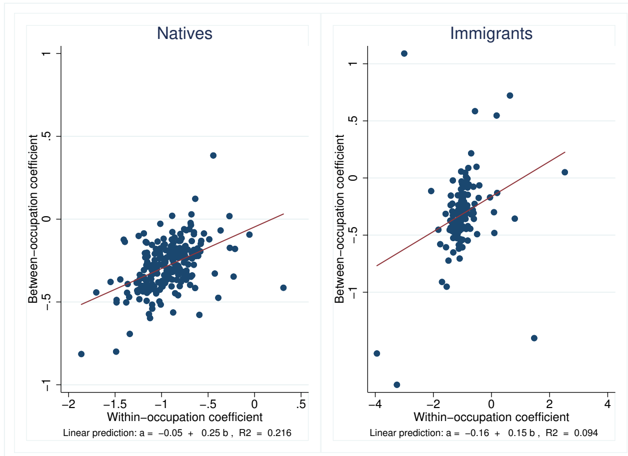
factual weights" panels in Figure 15). Thus, quantitatively, occupations appear as a relevant unit of analysis for examining wage differentials between individuals and their evolutions over time. It is increasingly true as the role of observable characteristics tends to decrease over time for both immigrants and natives (particularly when considering constant-population composition).

C.2 Between- and within-occupation wage changes

Consistently with our conceptual framework, we find a positive correlation between the two components of the price effect: higher values of the between coefficient are associated with higher values of the within coefficient, so that $Cov(a_j, b_j) > 0$, as predicted by our Roy-type model.

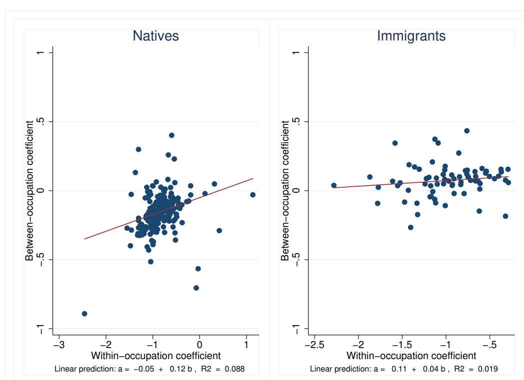
cell c and period t and Ψ_{ct} is the reweighting factor we estimate for each cell c at period t. More precisely, $\Psi_{ct} = \frac{\eta_c}{\eta_{ct}}$, where η_c is the share of workers (natives or immigrants) in the age-education cell c over the whole considered period (1994-2012) and η_{ct} is the share of workers (natives or immigrants) in the age-education cell c in period t.

Figure 16: Between- and within-occupation coefficients using LFS weights.



Notes: Natives' residual wages have been computed by including in the wage equation a full set of age*education dummies while immigrants' residual wages have been computed by including in the wage equation a full set of age*education*residence duration dummies and 27 origin country dummies. The between and within occupation coefficients have been computed considering 10 deciles. Composition effects are not controlled for.

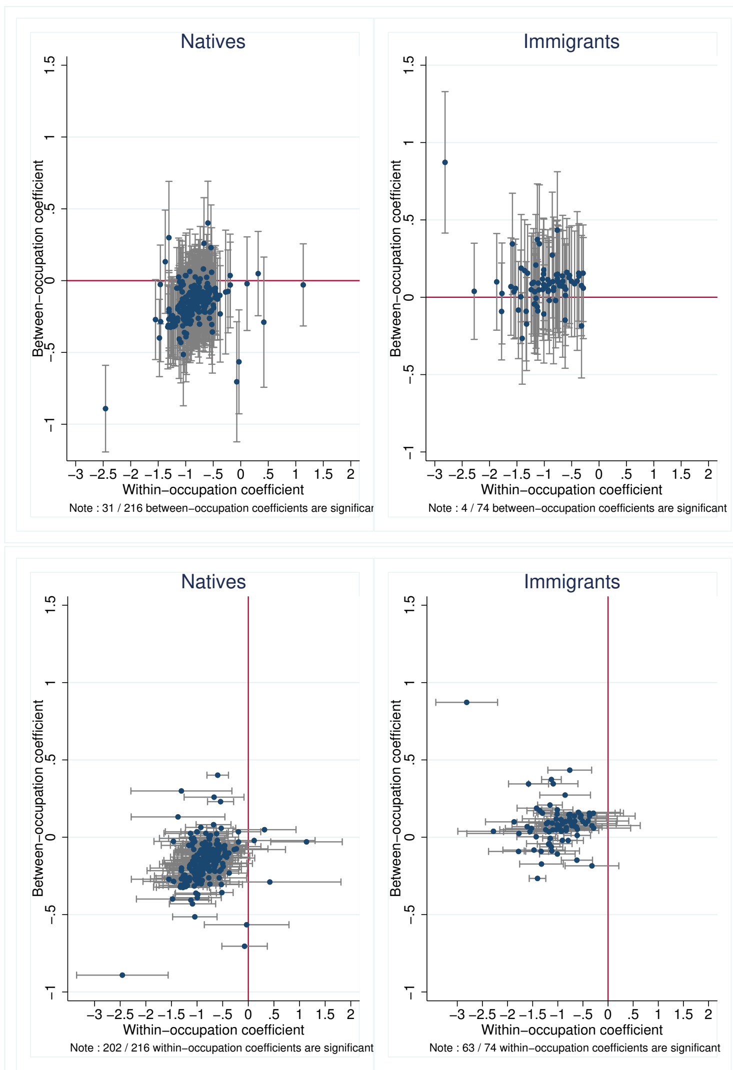
Figure 17: Between- and within-occupation coefficients with constant labor force composition.



Notes: Natives' residual wages have been computed by including in the wage equation a full set of age*education dummies while immigrants' residual wages have been computed by including in the wage equation a full set of age*education*residence duration dummies and 27 origin country dummies. The between and within occupation coefficients have been computed considering 9 wage deciles. Age*education composition within occupations is kept constant and equal to that of natives in period 1994-1996 for both immigrants and natives. For immigrants, their duration of residence composition is also kept constant and equal to that observed in 1994-1996.

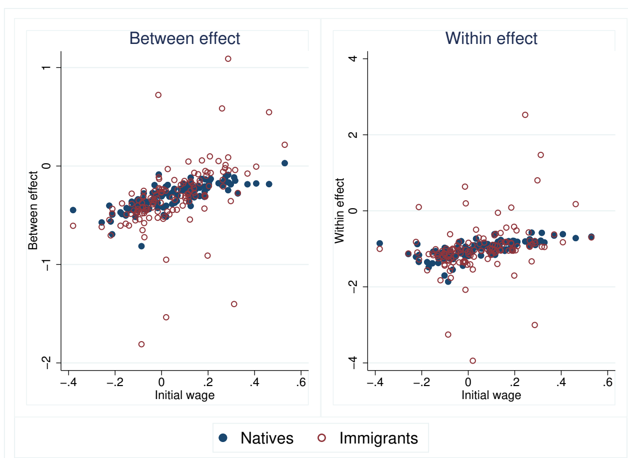
Evidently, an interesting test consists in reporting the confidence intervals together with the estimated between and within coefficients. Notice though that coefficients must be interpreted in relative terms since they are computed with respect to a reference occupation. This implies that when considering the between-coefficients (top panel) we conclude that average wage growth has not been significantly different between most of the considered jobs and the reference occupation. Average wage growth does not seem to have significantly differed among the whole set of occupations. In contrast, when focusing on the evolution of wage disparities within occupations (bottom panel), there are substantial differences across jobs. In some occupations, wage disparities have strongly increased, relatively to other occupations. This is not incompatible with the fact that average wage growth (between effect) remains not significantly different among many occupations.

Figure 18: Between- and within-occupation coefficients with 95% confidence intervals. Constant population composition.



Notes: Natives' residual wages have been computed by including in the wage equation a full set of age*education dummies while immigrants' residual wages have been computed by including in the wage equation a full set of age*education*residence duration dummies and 27 origin country dummies. The between and within occupation coefficients have been computed considering 9 wage deciles. Age*education composition within occupations is kept constant and equal to that of natives in period 1994-1996 for both immigrants and natives. For immigrants, their duration of residence composition is also kept constant and equal to that observed in 1994-1996.

Figure 19: Between- and within-occupation wage changes. Comparing Natives vs. Immigrants. Weights from the LFS



Notes: Natives' residual wages have been computed by including in the wage equation a full set of age*education dummies while immigrants' residual wages have been computed by including in the wage equation a full set of age*education*residence duration dummies and 27 origin country dummies. The between and within occupation coefficients have been computed considering 10 deciles. The X-axis stands for the occupational residual wage in period 1994-96 (common support for natives and immigrants). Composition effects are not controlled for.

D Estimations

Table 6: Immigrant effect in the between- and within-occupation wage changes, from 1994-96 to 2010-12. Pooled sample.

Dependent variables: Between- and within-occupation wage changes

	Between-occupation wage change					Within-occupation wage change				
Scenarios	Baseline	Weight 1	Weight 2	Weight 1	Weight 2	Baseline	Weight 1	Weight 2	Weight 1	Weight 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Immigrant	0.271***	0.279***	0.498***	0.434***	0.259***	-0.0855**	0.150***	0.134***	0.249***	-0.0405
	(0.0202)	(0.0185)	(0.0153)	(0.0208)	(0.0160)	(0.0393)	(0.0433)	(0.0373)	(0.0442)	(0.0439)
Population composition constant										
within group	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
within and across group	NO	NO	YES	NO	YES	NO	NO	YES	NO	YES
Control for residence duration	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES
Observations	250	186	180	164	146	250	186	180	164	146
R-squared	0.371	0.517	0.798	0.715	0.556	0.014	0.047	0.047	0.124	0.004

Notes: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. In all regressions we control for an occupation specific labor demand shift index (see text for details). Regressions are weighted using the initial period employment at the occupation of the corresponding nativity group. In all columns, natives' wage residuals have been computed by including in the wage equation a full set of age*education dummies. In columns (1)-(3) and (6)-(8) immigrants' wage residuals have been computed by including in the wage equation a full set of age*education dummies and 27 origin country dummies. In columns (4), (5), (9) and (10) wage residuals for immigrants have been computed by including a full set of dummies for age*educ*residence duration categories. In the weighting scenario Weight 1 population composition within occupations is kept constant as in the baseline for each nativity group. In the weighting scenario Weight 2, population composition within occupations is kept constant as that of natives in the baseline for both immigrants and natives. In columns (4), (5), (9) and (10), control for population composition effects includes immigrants' residence duration.

Table 7: Immigrant and task contribution to between- and within-occupation wage changes, from 1994-96 to 2010-12. Pooled sample.

Dependent variables: Between- and within-occupation wage changes

	Between-occupation wage change					Within-occupation wage change				
Scenarios	Baseline	Weight 1	Weight 2	Weight 1	Weight 2	Baseline	Weight 1	Weight 2	Weight 1	Weight 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Immigrant	0.278***	0.283***	0.502***	0.439***	0.261***	-0.0661*	0.161***	0.145***	0.262***	-0.0316
	(0.0170)	(0.0172)	(0.0140)	(0.0205)	(0.0134)	(0.0378)	(0.0434)	(0.0373)	(0.0458)	(0.0459)
Non-routine abstract	0.175***	0.121***	0.110**	0.132***	0.0740*	0.344***	0.407***	0.336***	0.394***	0.295**
	(0.0431)	(0.0432)	(0.0424)	(0.0458)	(0.0397)	(0.100)	(0.119)	(0.113)	(0.131)	(0.137)
Routine	-0.277***	-0.187***	-0.179***	-0.149***	-0.169***	-0.524***	-0.340**	-0.404***	-0.292*	-0.403***
	(0.0598)	(0.0514)	(0.0492)	(0.0529)	(0.0501)	(0.141)	(0.151)	(0.140)	(0.158)	(0.152)
Non-routine manual	0.311***	0.227***	0.208***	0.192***	0.259***	0.225**	0.114	0.211**	0.119	0.296***
	(0.0532)	(0.0466)	(0.0446)	(0.0482)	(0.0460)	(0.102)	(0.114)	(0.0993)	(0.115)	(0.101)
Population composition constant										
within group	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
within and across group	NO	NO	YES	NO	YES	NO	NO	YES	NO	YES
Control for residence duration	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES
Observations	248	184	178	162	144	248	184	178	162	144
R-squared	0.526	0.619	0.841	0.766	0.685	0.183	0.183	0.191	0.229	0.110

Notes: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. In all regressions we control for an occupation specific labor demand shift index (see text for details). Regressions are weighted using the initial period employment at the occupation of the corresponding nativity group. In all columns, natives' wage residuals have been computed by including in the wage equation a full set of age*education dummies. In columns (1)-(3) and (6)-(8) immigrants' wage residuals have been computed by including in the wage equation a full set of age*education dummies and 27 origin country dummies. In columns (4), (5), (9) and (10) wage residuals for immigrants have been computed by including a full set of dummies for age*educ*(residence duration) categories. In the weighting scenario Weight 1, population composition within occupations is kept constant as in the baseline for each nativity group. In the weighting scenario Weight 2, population composition within occupations is kept constant as that of natives in the baseline for both immigrants and natives. In columns (4), (5), (9) and (10) control for population composition effects includes immigrants' residence duration.

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Table 8: Task contribution to the estimated differential in between- and within-occupation wage changes for natives and immigrants, from 1994-96 to 2010-12.

Dependent variables: Between- and within-occupation wage changes

	Between-occupation wage change					Within-occupation wage change				
Scenarios	Baseline	Weight 1	Weight 2	Weight 1	Weight 2	Baseline	Weight 1	Weight 2	Weight 1	Weight 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Non-routine abstract	0.135**	0.104	0.200**	0.133	0.0892	-0.119	-0.204	-0.115	-0.321	0.110
	(0.0671)	(0.123)	(0.0776)	(0.172)	(0.0561)	(0.178)	(0.216)	(0.243)	(0.265)	(0.284)
Routine	-0.0909	-0.0414	0.0584	0.123	0.0291	0.337*	0.679**	0.451*	0.692**	0.226
	(0.0896)	(0.138)	(0.125)	(0.162)	(0.0736)	(0.202)	(0.271)	(0.247)	(0.309)	(0.315)
Non-routine manual	0.0661	0.0314	-0.200*	-0.193	-0.0873	-0.277	-0.862***	-0.591**	-1.015***	-0.598*
	(0.0817)	(0.147)	(0.108)	(0.201)	(0.0638)	(0.186)	(0.288)	(0.238)	(0.334)	(0.320)
Population composition constant										
within group	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
within and across group	NO	NO	YES	NO	YES	NO	NO	YES	NO	YES
Control for residence duration	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES
Observations	124	92	89	81	72	124	92	89	81	72
R-squared	0.032	0.023	0.123	0.038	0.035	0.018	0.119	0.081	0.142	0.113

Notes: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. In all regressions we control for an occupation specific labor demand shift index (see text for details). Regressions are weighted using the initial period employment level. In all columns, natives' wage residuals have been computed by including in the wage equation a full set of age*education dummies. In columns (1)-(3) and (6)-(8) immigrants' wage residuals have been computed by including in the wage equation a full set of age*education dummies and 27 country of birth dummies. In columns (4), (5), (9) and (10) wage residuals for immigrants have been computed by including a full set of dummies for age*educ*(residence duration) categories. In the weighting scenario Weight 1, population composition within occupations is kept constant as in the baseline for each nativity group. In the weighting scenario Weight 2, population composition within occupations is kept constant as that of natives in the baseline for both immigrants and natives. In columns (4), (5), (9) and (10) control for population composition effects includes immigrants' residence duration.

Table 9: Immigrant effect net of the minimum wage in the between- and within-occupation wage changes, from 1994-96 to 2010-12. Pooled sample.

Dependent variables: Between- and within-occupation wage changes

	Between-occupation wage change				Within-occupation wage change			
Scenarios	Weight 1	Weight 2	Weight 1	Weight 2	Weight 1	Weight 2	Weight 1	Weight 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrant	0.339***	0.394***	0.241***	0.128***	0.148***	0.270***	0.519***	0.123***
	(0.0251)	(0.0239)	(0.0234)	(0.0208)	(0.0486)	(0.0544)	(0.0427)	(0.0417)
Population composition constant								
within group	YES	YES	YES	YES	YES	YES	YES	YES
within and across group	NO	YES	NO	YES	NO	YES	NO	YES
Control for residence duration	NO	NO	YES	YES	NO	NO	YES	YES
Observations	160	150	154	138	160	150	154	138
R-squared	0.470	0.552	0.335	0.145	0.042	0.134	0.427	0.047

Notes: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. In all regressions we control for an occupation specific labor demand shift index (see text for details). Regressions are weighted using the initial period employment level. In all columns, natives' wage residuals have been computed by including in the wage equation a full set of age*education dummies. In columns (1)-(3) and (6)-(8) immigrants' wage residuals have been computed by including in the wage equation a full set of age*education dummies and 27 country of birth dummies. In columns (4), (5), (9) and (10) wage residuals for immigrants have been computed by including a full set of dummies for age*educ*(residence duration) categories. In the weighting scenario Weight 1, population composition within occupations is kept constant as in the baseline for each nativity group. In the weighting scenario Weight 2, population composition within occupations is kept constant as that of natives in the baseline for both immigrants and natives. In columns (4), (5), (9) and (10) control for population composition effects includes immigrants' residence duration.

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